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High-Dimensional Multi-Objective Lightweight Design of Commercial Vehicle Doors

Cai-Feng Sun[1,*], Ling-Han Meng[1]
[1]Jiangsu Vocational College of Electronics and Information, Huaian 223003, P. R. China
160608@jsei.edu.cn, meng_7819@163.com

Yi Zhang[1,2]
[1]Jiangsu Vocational College of Electronics and Information, Huaian 223003, P. R. China
[2]Dhonburi Rajabhat University, Bangkok 10600, Thailand
zy20241024@163.com

*Corresponding author: Cai-Feng Sun

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Abstract. *The lightweight design of commercial vehicle doors faces the challenge of high-dimensional multi-objective optimisation, and it is difficult for traditional methods to effectively balance the weight reduction objectives and performance requirements. To solve this problem, a high-dimensional multi-objective optimisation method is proposed. Firstly, the problem dimensions are effectively reduced by variable screening through global sensitivity analysis based on the Sobol method. Secondly, the Kriging agent model is used to replace the time-consuming finite element analysis. Finally, the improved NSGA-III introduces the adaptive cross-variable operation and the decision-making framework that hinges on a reference point. The results show that compared with the traditional NSGA-II, the improved NSGA-III improves the hypervolume metric (HV) by 16.02%, the distribution uniformity metric (Spacing) by 29.94%, and the convergence metric (IGD) by 33.25%. The optimised door mass is reduced by 14.46%.*
Keywords: Vehicle door; Lightweighting; Multi-objective optimisation; NSGA-III; Kriging agent.

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1. **Introduction.** As an important tool for logistics and transport, the fuel economy and load carrying capacity of commercial vehicles have a direct impact on operating costs and efficiency [1, 2]. As a key component of the vehicle body structure, the door accounts for 5–10% of the total vehicle mass and has a significant impact on vehicle performance [3, 4]. Therefore, the lightweight design of commercial vehicle doors has important economic and environmental benefits and has attracted extensive attention from both academia and industry.

However, the lightweight design of doors for commercial vehicles faces unique challenges [5]. Compared with passenger cars, commercial vehicles require higher strength, stiffness and durability of doors, while cost control and feasibility of mass production need to be considered. This requires the simultaneous consideration of multiple performance indicators and constraints in the lightweighting process, forming a typical high-dimensional multi-objective optimisation problem [6]. How to achieve the maximum weight reduction under the premise of guaranteeing the performance indexes of the door has become a key challenge in the current research.

1.1. **Related work.** The traditional methods of automotive lightweight design mainly include material substitution and structural optimization. Cavazzuti et al. [7] proposed a topology optimization-based lightweighting method for body structure, which achieved 15% mass reduction by optimizing the material distribution, but the method requires a high manufacturing process. Cecchel [8] investigated the application of high-strength steels for door lightweighting, which achieved 10% weight reduction, but the increase in material cost limited its large-scale application in commercial vehicles.

In recent years, the combination of parametric modelling and simulation analysis has become the mainstream of vehicle lightweight design. Sun et al. [9] introduced machine learning algorithms into the lightweight design of vehicles, and established a mapping model of plate thickness and performance, with a weight reduction effect of 12%. Yılmaz et al. [10] proposed a door lightweighting method based on parametric CAD model and finite element analysis, and achieved 8% weight reduction by optimising key dimensional parameters. However, the above methods often have difficulties in balancing different performance metrics when dealing with multi-objective optimisation problems.

The multi-objective optimization technique shows great potential in the lightweight design of vehicle doors. Khettabi et al. [11] proposed a multi-objective optimization method based on the NSGA-II algorithm, which simultaneously considered the mass, stiffness and modal objectives, and achieved a better compromise. Zapotecas-Martínez et al. [12] combined the agent model with multi-objective optimisation to improve the solution efficiency, but the model accuracy and robustness still need to be improved. However, this method is computationally inefficient when dealing with high-dimensional design variables.

1.2. **Contribution.** Through the analysis of the above studies, it can be seen that the existing commercial vehicle door lightweighting methods usually focus on the optimisation of a single performance index, and it is difficult to deal with the multi-objective trade-off problem effectively. The complex coupling relationship between different performance indicators makes the model often led to the deterioration of other indicators when optimising one indicator. The high-dimensional design variable space increases the complexity of the problem, and traditional optimisation algorithms are prone to fall into local optimal solutions or converge inefficiently when dealing with a large number of design variables. To solve the above problems, this study proposes a high-dimensional multi-objective optimisation on the improved NSGA-III to enhance the lightweight design of commercial vehicle doors.

The main innovations and contributions of this work include:

(1) To address the challenges of multi-objective optimisation, the improved NSGA-III employs a dynamic crossover and mutation operations, which are able to better balance the trade-offs between different performance metrics, thus enhancing the optimisation ability of the model in dealing with complex constraints. This improvement is particularly significant in high-dimensional multi-objective optimisation problems, which effectively solves the problem of computational inefficiency of the NSGA-II proposed by Khettabi et al. [11] when dealing with high-dimensional design variables.

(2) To address the complexity of high-dimensional design space, this study proposes a variable screening method based on sensitivity analysis, which effectively reduces the dimensionality of the problem by identifying the key variables that have the most significant impact on the objective function. Meanwhile, a high-precision proxy model is used to replace the time-consuming finite element analysis, which significantly

improves the optimisation efficiency. This approach effectively overcomes the shortcomings of the proxy model proposed by Zapotecas-Martínez et al. [12] in terms of accuracy and robustness, and provides an efficient and reliable solution strategy for high-dimensional multi-objective optimisation problems.

2. Problem definition and methodological overview.

2.1. Description of lightweight design problems for commercial vehicle doors.

The lightweight design problem of a commercial vehicle door is essentially a multi-objective optimisation problem, which needs to minimise the mass under the premise of ensuring the performance of the door. In this study, the side sliding door of a commercial vehicle is taken as the research object, and a finite element model containing the main structures such as inner and outer panels, reinforcing bars and impact beams is established. The model is meshed with a four-node shell cell with a cell size of 8 mm. Welded joints are simulated with ACM cells, and rigid joints are simulated with RBE2 cells [13]. The material properties are set as density $\rho = 7850$ kg/m^3, modulus of elasticity $E = 210$ GPa, Poisson's ratio $\nu = 0.3$. The finite element model of the vehicle side sliding door is shown in Figure 1.

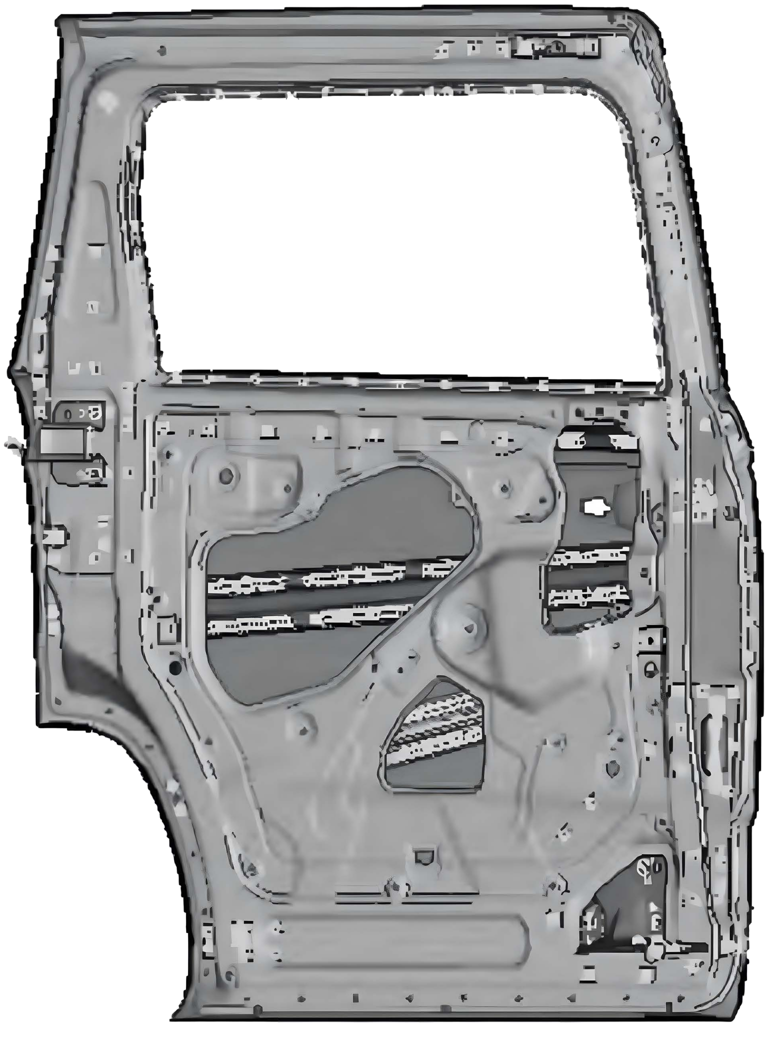

Figure 1. Finite element model of side sliding door

Define the vector of design variables $\mathbf{x} = [x_1, x_2, \ldots, x_n]^T$, where x_i denotes the thickness of the i-th component and n is the total number of design variables [14]. The optimisation objectives include door mass $M(\mathbf{x})$, first order bending mode frequency $f_1(\mathbf{x})$, vertical stiffness $K_v(\mathbf{x})$ and torsional stiffness $K_t(\mathbf{x})$. The constraints include the lower limit values of each performance index and the range of values of the design variables.

The multi-objective optimisation problem can be formulated as:

$$\begin{aligned} \min \quad & [M(\mathbf{x}), -f_1(\mathbf{x}), -K_v(\mathbf{x}), -K_t(\mathbf{x})] \\ \text{s.t.} \quad & f_1(\mathbf{x}) \geq f_{1,min}; K_v(\mathbf{x}) \geq K_{v,min}; K_t(\mathbf{x}) \geq K_{t,min}; x_i^L \leq x_i \leq x_i^U \end{aligned} \tag{1}$$

where $f_{1,min}$, $K_{v,min}$ and $K_{t,min}$ are the minimum permissible values of the first-order bending modal frequency, vertical stiffness and torsional stiffness, respectively; and x_i^L and x_i^U are the lower and upper bounds of the i-th design variable, respectively.

2.2. **High-dimensional multi-objective optimisation framework.** A typical high-dimensional problem is formed due to the complex structure of commercial vehicle doors and the large number of design variables. Traditional methods often face challenges such as low computational efficiency and the tendency to fall into local optimisation when dealing with such problems. Aiming at lightweight design of commercial vehicle doors, an integrated optimisation framework is proposed in this study, as shown in Figure 2. The framework aims to effectively deal with the challenges of high-dimensional design space, multi-objective trade-offs and computational efficiency, and contains three key components.

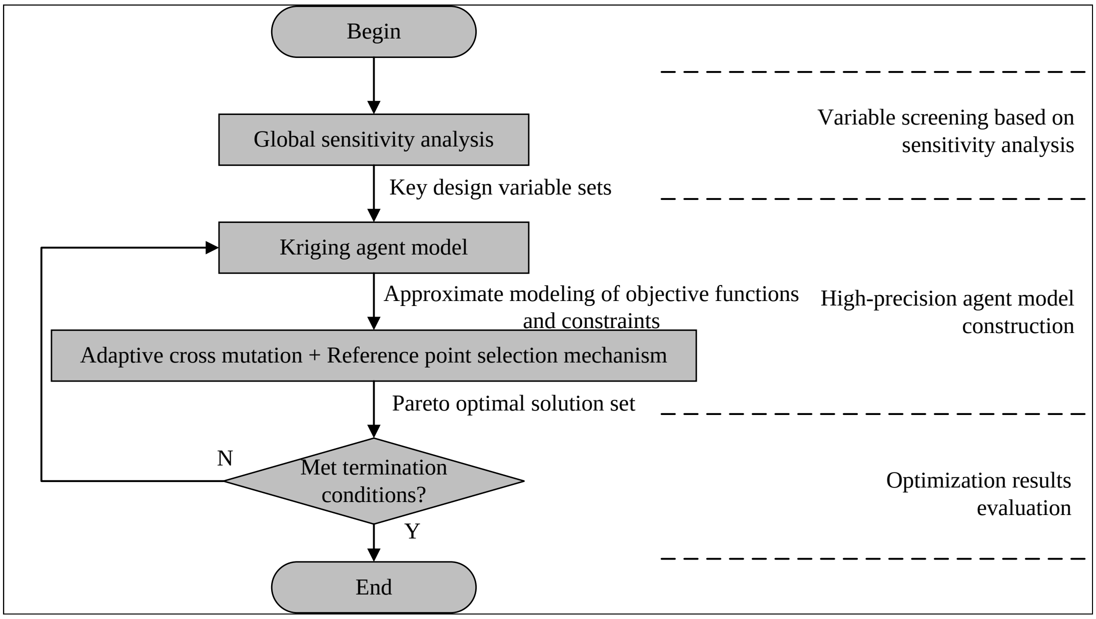

Figure 2. High-dimensional multi-objective optimisation framework

First, a variable screening method based on sensitivity analysis was used. By assessing the degree of influence of each design variable on the objective function, the most critical set of variables is identified and selected. This step effectively reduces the dimensionality of the problem and lays the foundation for subsequent optimisation.

Secondly, high-precision proxy models are constructed to replace time-consuming finite element analyses. Advanced proxy modelling techniques are used to build approximate models of the objective function and constraints to significantly improve computational efficiency.

Finally, the improved NSGA-III algorithm is applied to solve the multi-objective optimisation problem. The uniformity of the distribution of the algorithm's search capability and solution in high-dimensional objective space is enhanced by introducing an adaptive strategy and an improved selection mechanism.

These three components are organically combined to form a complete optimisation process: firstly, the variables are screened to reduce the problem dimensions; then an agent model is constructed based on the screened variables; finally, the improved NSGA-III is used to optimise the solution on the agent model. The framework effectively improves the optimisation efficiency and the quality of the solution for the lightweight design of commercial vehicle doors by integrating multiple advanced techniques.

3. Variable screening based on sensitivity analysis.

3.1. **Global sensitivity analysis (GSA).** GSA is an effective tool for identifying key design variables in the lightweight design of commercial vehicle doors [15, 16]. In this study, GSA was conducted using the variance-based Sobol method, which is capable of comprehensively assessing the effects of parameters influencing the objective function, including main and interaction effects. GSA is able to assess the degree of influence of each input variable on the output response, helping to identify the key variables that have the greatest impact on door lightweighting. Screening out the important variables through GSA can reduce the complexity of the model and improve the optimization efficiency.

For a given objective function $Y = f(\mathbf{x})$, where $\mathbf{x} = [x_1, x_2, \ldots, x_n]^T$ is a vector of design variables, and the Sobol method decomposes the function variance into a sum of sensitivity indicators of each order:

$$V(Y) = \sum_{i=1}^{n} V_i + \cdots + \sum_{1 \le i < j \le n} V_{ij} + V_{1,2,\ldots,n} \tag{2}$$

where V_i denotes the variance of the main effect of the i-th variable; V_{ij} denotes the variance of the second-order interaction effect of variables i and j, and so on.

Based on the variance decomposition, the first-order Sobol indicator S_i and the total effect indicator ST_i for the i-th variable are defined as:

$$S_i = \frac{V_i}{V(Y)}, \quad ST_i = \frac{V_{T_i}}{V(Y)} \tag{3}$$

where V_{T_i} contains all variance contributions associated with the variable i.

As to enhance the computational efficiency, the Monte Carlo integration is used to estimate the Sobol indicator in this study. Two independent sample matrices $\mathbf{A}$ and $\mathbf{B}$ are first generated, each containing N sample points. Then n matrices $\mathbf{A}_i^B$ are constructed, where the i-th column is from matrix $\mathbf{B}$ and the remaining columns are from matrix $\mathbf{A}$. The estimation equations for the first-order and total effects indicators are:

$$\widehat{S}_i = \frac{\frac{1}{N}\sum_{j=1}^{N} f(\mathbf{B})_j (f(\mathbf{A}_i^B)_j - f(\mathbf{A})_j)}{\frac{1}{N}\sum_{j=1}^{N} f(\mathbf{B})_j^2 - f_0^2} \tag{4}$$

$$\widehat{ST}_i = 1 - \frac{\frac{1}{N}\sum_{j=1}^{N} f(\mathbf{A})_j (f(\mathbf{A}_i^B)_j - f(\mathbf{B})_j)}{\frac{1}{N}\sum_{j=1}^{N} f(\mathbf{B})_j^2 - f_0^2} \tag{5}$$

where f_0 is the mean of the function f.

By calculating S_i and ST_i for each design variable, the degree of its influence on the objective function can be comprehensively assessed. This GSA-based variable screening method not only considers the main effects of the variables, but also includes the higher-order interaction effects, effectively overcoming the limitations of the traditional local sensitivity analysis methods. Meanwhile, the introduction of Monte Carlo integration significantly improves the computational efficiency, enabling the method to be applied to high-dimensional design problems.

This comprehensive and efficient GSA approach provides a reliable basis for subsequent variable screening, which helps to simplify the problem's scope to boost the optimization performance. In the next section, a specific variable screening strategy is developed based on the GSA results.

3.2. **Key variable identification and screening strategies.** Based on the results of GSA, this section proposes an effective strategy for identifying and screening key variables. The strategy integrates the main and interaction effects of variables and the sensitivity characteristics of multiple objective functions.

First, for each objective function $f_k(\mathbf{x})$, $k = 1, 2, \ldots, K$, calculate the first-order Sobol indicator S_i^k and the total effect indicator ST_i^k for all design variables. Define the composite sensitivity indicator CS_i as:

$$CS_i = \sum_{k=1}^{K} w_k \cdot (S_i^k + ST_i^k) \tag{6}$$

where w_k is the weight of the objective function f_k satisfying $\sum_{k=1}^{K} w_k = 1$. The choice of weights can be adjusted according to the needs of specific problems.

Next, the cumulative contribution rate method was used to screen the key variables. The design variables were ranked in descending order of CS_i and the cumulative contribution rate CCR_m was defined as:

$$CCR_m = \frac{\sum_{i=1}^{m} CS_i}{\sum_{i=1}^{n} CS_i} \tag{7}$$

where m is the number of variables selected and n is the total number of variables.

A threshold η is set (usually taken as 0.8 to 0.9), the smallest m value that satisfies the condition $CCR_m \geq \eta$ is selected, and the corresponding m variables are used as key variables. This approach ensures that the set of variables selected explains most of the response variance.

To further consider the correlation between variables, a correlation threshold ρ_{th} is introduced. For any two variables x_i and x_j, if their correlation coefficients ρ_{ij} satisfy $|\rho_{ij}| > \rho_{th}$, then the larger of CS_i and CS_j is selected to be retained, and the smaller one is excluded. This step helps to reduce redundant variables and improve the explanatory power of the model.

Finally, to ensure that potentially important variables are not missed, expert knowledge is introduced to assist in the screening. Based on design experience and engineering practice, variables that are considered important a priori can be included in the set of key variables, even if they have relatively low CS_i values.

The above steps lead to the final set of key variables $\mathbf{x}' = [x'_1, x'_2, \ldots, x'_m]^T$, where $m < n$. This screening strategy, which combines quantitative analysis and expert knowledge, not only effectively reduces the problem dimensionality, but also ensures that the most influential design variables are retained.

The set of key variables obtained from the screening will be used in the subsequent agent model construction and optimisation process. By reducing the problem dimensions, the required sample size can be significantly reduced, enhancing the precision of the agent model and the efficiency of the optimization process. At the same time, focusing on key variables also helps engineers to better understand and control the design process.

4. **Improvement of NSGA-III algorithm.**

4.1. **Adaptive crossover and mutation operations.** In order to improve the performance of the NSGA-III in high-dimensional multi-objective optimisation, an adaptive crossover and mutation operation strategy is proposed in this section. The strategy balances global exploration and local exploitation capabilities during the optimisation process by dynamically adjusting the crossover probability and mutation probability, thus improving the convergence speed and diversity of the algorithm.

First, define the adaptive crossover probability p_c and the variance probability p_m as a function of the current iteration number t:

$$p_c = p_{c,min} + (p_{c,max} - p_{c,min}) \cdot e^{-\alpha t/T}, \quad p_m = p_{m,min} + (p_{m,max} - p_{m,min}) \cdot e^{-\beta t/T} \tag{8}$$

where $p_{c,min}$ and $p_{c,max}$ are the lower and upper bounds of the crossover probability, $p_{m,min}$ and $p_{m,max}$ are the lower and upper bounds of the variance probability, T is the maximum number of iterations, and α and β are the control parameters used to regulate the rate of probability change.

To further improve the adaptability of the algorithm, a dynamic adjustment mechanism based on population diversity is introduced. The population diversity indicator D was defined as:

$$D = \frac{1}{N} \sum_{i=1}^{N} \min_{j \neq i} d_{ij} \tag{9}$$

where N is the population size; d_{ij} is the Euclidean distance between individuals i and j in the decision space.

Further adjustments for crossover and variance probabilities based on diversity metrics:

$$p_{c'} = p_c \cdot (1 + \gamma_c \cdot (D_{max} - D)/D_{max}), \quad p_{m'} = p_m \cdot (1 + \gamma_m \cdot (D_{max} - D)/D_{max}) \tag{10}$$

where D_{max} is the preset maximum diversity threshold; γ_c and γ_m are the adjustment coefficients. When the population diversity decreases, the crossover and mutation probabilities will increase accordingly to promote the exploratory ability of the population.

In the crossover operation, a modified Simulated Binary Crossover (SBX) method is used. For the parent individuals $\mathbf{x}_1$ and $\mathbf{x}_2$, the children $\mathbf{y}_1$ and $\mathbf{y}_2$ are generated by the formula:

$$y_{1,i} = 0.5[(1 + \beta_i)x_{1,i} + (1 - \beta_i)x_{2,i}], \quad y_{2,i} = 0.5[(1 - \beta_i)x_{1,i} + (1 + \beta_i)x_{2,i}] \tag{11}$$

where β_i is a function of the distribution index η_c.

$$\beta_i = \begin{cases} (2u_i)^{1/(\eta_c+1)}, & \text{if } u_i \leq 0.5 \\ [2(1 - u_i)]^{-1/(\eta_c+1)}, & \text{otherwise} \end{cases} \tag{12}$$

where u_i is a random number in the interval $[0, 1]$.

The mutation operation uses a modified polynomial mutation method. For the individual $\mathbf{x}$, the generated formula for the mutated individual $\mathbf{y}$ is:

$$y_i = x_i + \delta_i(x_i^U - x_i^L) \tag{13}$$

where x_i^U and x_i^L are the upper and lower bounds of the i-th decision variable, respectively; and δ_i is a function of the distribution index η_m.

$$\delta_i = \begin{cases} [2r_i + (1 - 2r_i)(1 - \Delta_i)^{\eta_m+1}]^{1/(\eta_m+1)} - 1, & \text{if } r_i < 0.5 \\ 1 - [2(1 - r_i) + 2(r_i - 0.5)(1 - \Delta_i)^{\eta_m+1}]^{1/(\eta_m+1)}, & \text{otherwise} \end{cases} \tag{14}$$

where r_i is a random number in the interval $[0, 1]$; $\Delta_i = (x_i - x_i^L)/(x_i^U - x_i^L)$.

This adaptive crossover and mutation operation strategy is able to dynamically adjust the parameters of the genetic operators according to the different stages of the optimisation process and the diversity state of the population. At the initial stage of optimisation, higher crossover and mutation probabilities help global exploration; as iteration proceeds, progressively lower probabilities facilitate local exploitation. Meanwhile, the adjustment mechanism based on population diversity further enhances the adaptive capability of the algorithm. This improvement significantly provides a powerful optimisation tool for lightweight design of commercial vehicle doors.

4.2. **Reference point-based selection mechanism.** One of the core features of the NSGA-III algorithm is the reference point-based selection mechanism, which is improved in this section to better suit the high-dimensional multi-objective optimisation problem in the lightweight design of commercial vehicle doors. The improved selection mechanism is able to obtain a more uniformly distributed set of Pareto optimal solutions in the high-dimensional objective space.

First, a set of uniformly distributed reference points $\mathbf{W} = \{\mathbf{w}_1, \mathbf{w}_2, \ldots, \mathbf{w}_H\}$, where H is the number of reference points. For each solution $\mathbf{x}$, compute its vertical distance to each reference line:

$$d_\perp(\mathbf{x}, \mathbf{w}_j) = \|\mathbf{f}(\mathbf{x}) - (\mathbf{f}(\mathbf{x})^T \mathbf{w}_j)\mathbf{w}_j\| \tag{15}$$

where $\mathbf{f}(\mathbf{x})$ is the vector of objective function values for solving $\mathbf{x}$; and $\mathbf{w}_j$ is the j-th reference point.

In order to deal with the problem of "dimensional catastrophe" in high dimensional spaces, an adaptive weighting factor λ_j is introduced:

$$\lambda_j = \frac{1}{\sum_{i=1}^{N} e^{-\gamma d_\perp(\mathbf{x}_i, \mathbf{w}_j)}} \tag{16}$$

where N is the population size and γ is the control parameter. This weighting design can dynamically adjust the importance of the reference point according to the distribution of solutions.

In the selection process, the first $k-1$ ranks of solutions obtained from the non-dominated ordering are first kept directly. For the k-th rank of solutions, they are selected based on their associativity with the reference point to fill the remaining positions. The degree of association is defined as:

$$\text{Association}(\mathbf{x}, \mathbf{w}_j) = \lambda_j \cdot e^{-\gamma d_\perp(\mathbf{x}, \mathbf{w}_j)} \tag{17}$$

The selection process employs a greedy strategy, where the solution-reference point pair with the highest correlation and not yet selected is selected each time until the population size reaches a predefined value.

To further improve the performance in high dimensional spaces, an adaptive reference point adjustment mechanism is introduced. Define the crowding degree C_j of the reference point as:

$$C_j = \sum_{i=1}^{N} I(\mathbf{x}_i, \mathbf{w}_j) \tag{18}$$

where $I(\mathbf{x}_i, \mathbf{w}_j)$ is the indicator function, which is 1 when $\mathbf{x}_i$ is associated with $\mathbf{w}_j$, 0 otherwise.

Dynamic adjustment of reference points based on congestion:

$$\mathbf{w}_{j'} = \mathbf{w}_j + \eta \cdot (C_{max} - C_j) \cdot \mathbf{v}_j \tag{19}$$

where $\mathbf{w}_{j'}$ is the adjusted reference point; C_{max} is the maximum crowding, η is the learning rate; and $\mathbf{v}_j$ is the adjusted direction vector, which is determined by the distribution of the solutions associated with $\mathbf{w}_j$ in the current population.

This improved reference point-based selection mechanism has the following advantages:

1. Adaptive weighting factors can effectively deal with the "sparsity" problem in high-dimensional spaces;
2. The definition of correlation considers the importance of knowing the distance to the reference point and the importance of the reference point to help obtain a more homogeneous solution set;
3. The adaptive reference point adjustment mechanism can dynamically adjust the search direction according to the distribution of the solution to enhance the exploration ability in high-dimensional space.

With these improvements, the NSGA-III is able to handle the high-dimensional multi-objective optimisation problems in the lightweight design of commercial vehicle doors more efficiently, obtaining a more diversified and uniformly distributed set of Pareto optimal solutions. This provides richer choices for engineering decisions and helps to find the optimal balance between quality, performance and cost.

5. High-precision agent model construction.

5.1. Kriging agent model fundamentals.

The Kriging agent model is an interpolation method based on Gaussian processes that performs well in dealing with high-dimensional nonlinear problems. The Kriging model is used as an alternative to time-consuming finite element analysis in the lightweight design of commercial vehicle doors to significantly improve the optimisation efficiency.

For a given sample set $\{(\mathbf{x}_i, y_i), i = 1, \ldots, n\}$, where $\mathbf{x}_i \in \mathbb{R}^m$ is the m-dimensional input vector and $y_i \in \mathbb{R}$ is the corresponding output value, the Kriging model assumes that the true function $f(\mathbf{x})$ can be expressed as:

$$f(\mathbf{x}) = \mu(\mathbf{x}) + Z(\mathbf{x}) \tag{20}$$

where $\mu(\mathbf{x})$ is the deterministic trend function and $Z(\mathbf{x})$ is the zero-mean Gaussian stochastic process with covariance function:

$$\mathrm{Cov}[Z(\mathbf{x}_i), Z(\mathbf{x}_j)] = \sigma^2 R(\mathbf{x}_i, \mathbf{x}_j, \boldsymbol{\theta}) \tag{21}$$

where σ^2 is the process variance, $R(\cdot)$ is the correlation function, and $\boldsymbol{\theta}$ is the hyperparameter.

Selection of Gaussian correlation function in lightweight design of commercial vehicle doors:

$$R(\mathbf{x}_i, \mathbf{x}_j, \boldsymbol{\theta}) = \exp\left(-\sum_{k=1}^{m} \theta_k (x_{ik} - x_{jk})^2\right) \tag{22}$$

The predicted value $\hat{f}(\mathbf{x})$ and the predicted variance $s^2(\mathbf{x})$ of the Kriging model are, respectively:

$$\hat{f}(\mathbf{x}) = \mu + \mathbf{r}^T(\mathbf{x})\mathbf{R}^{-1}(\mathbf{y} - \mathbf{1}\mu) \tag{23}$$

$$s^2(\mathbf{x}) = \sigma^2(1 - \mathbf{r}^T(\mathbf{x})\mathbf{R}^{-1}\mathbf{r}(\mathbf{x})) \tag{24}$$

where $\mathbf{R}$ is the correlation matrix between sample points, $\mathbf{y} = [y_1, \ldots, y_n]^T$, and $\mathbf{1}$ is the all-1 vector.

The hyperparameters $\boldsymbol{\theta}$ are obtained by maximum likelihood estimation with an objective function:

$$\max_{\boldsymbol{\theta}} \left\{-\frac{n}{2}\ln(\sigma^2) - \frac{1}{2}\ln(|\mathbf{R}|)\right\} \tag{25}$$

5.2. **Adaptive sampling strategy.** To enhance the Kriging model in high dimensional space, this study proposes an adaptive sampling strategy. The strategy combines exploratory and exploitative aspects and can efficiently improve the model quality with limited computational resources.

The adaptive sampling process uses the Expected Improvement (EI) criterion to select new sampling points. For the minimisation problem, EI is defined as:

$$EI(\mathbf{x}) = (f_{min} - \hat{f}(\mathbf{x}))\Phi\left(\frac{f_{min} - \hat{f}(\mathbf{x})}{s(\mathbf{x})}\right) + s(\mathbf{x})\phi\left(\frac{f_{min} - \hat{f}(\mathbf{x})}{s(\mathbf{x})}\right) \tag{26}$$

where f_{min} is the current optimal function value; $\Phi(\cdot)$ and $\phi(\cdot)$ are the cumulative distribution function and the probability density function for a standard Gaussian distribution, respectively.

To deal with the sampling challenge in high-dimensional spaces, a local search strategy is introduced. In each iteration, k candidate points with the highest EI values are selected and then local optimisation is performed in the neighbourhood of these points:

$$\mathbf{x}_{new} = \arg \max_{\mathbf{x}\in\mathcal{N}(\mathbf{x}_c)} EI(\mathbf{x}) \tag{27}$$

where $\mathcal{N}(\mathbf{x}_c)$ denotes the neighbourhood of the candidate point $\mathbf{x}_c$.

To balance computational overhead and model accuracy, a dynamic stopping criterion is used. Relative Improvement (RI) metrics are defined:

$$RI = \frac{|f_{min}^{(t)} - f_{min}^{(t-1)}|}{|f_{min}^{(t-1)}|} \tag{28}$$

where $f_{min}^{(t)}$ is the optimal function value after the t-th iteration. The sampling process is stopped when the RI value of n_{stop} consecutive iterations is less than the preset threshold ϵ.

This adaptive sampling strategy can effectively allocate computational resources in high-dimensional space, avoiding the "dimensional disaster" problem of traditional uniform sampling methods in high-dimensional cases. By combining global exploration and local optimisation, this strategy can rapidly enhance the Kriging model in critical regions, providing a reliable proxy model for the lightweight design of commercial vehicle doors.

6. Experimental design and analysis of results.

6.1. **Experimental set-up.** To demonstrate the efficacy of the suggested approach for high-dimensional multi-objective optimization in the lightweight design of commercial vehicle doors, this section elaborates on the experimental setup. The experimental object is the side sliding door of a certain commercial vehicle, which contains the main structural components such as inner and outer panels, reinforcement bars, and impact beams.

The initial finite element model contains 23 design variables corresponding to the plate thicknesses of the different components. The range of the variables is set to $\pm 30\%$ of the original thickness. The optimisation objective functions include: door mass $M(\mathbf{x})$, first order bending mode frequency $f_1(\mathbf{x})$, vertical stiffness $K_v(\mathbf{x})$ and torsional stiffness $K_t(\mathbf{x})$. The constraints are defined as follows:

$$f_1(\mathbf{x}) \geq 25 \text{ Hz}, K_v(\mathbf{x}) \geq 2000 \text{ N/mm}; K_t(\mathbf{x}) \geq 1000 \text{ Nm/deg} \tag{29}$$

GSA was conducted using the Sobol method with the sample size set at $10000\times(2m+2)$, where m is the number of design variables. The variable screening threshold η was set at 0.85 and the correlation threshold ρ_{th} was set at 0.9.

The initial samples for the Kriging agent model are generated using the Latin hypercubic sampling method with a sample size of $10m$. During the adaptive sampling process, 5 candidate points are selected in each iteration, and the radius of the local search neighbourhood is set to 10% of the variable range. The dynamic stopping criterion parameters are set to $N_{stop} = 5$ and $\epsilon = 0.01$.

The parameters of the improved NSGA-III are set as follows: adaptive parameters $\alpha = 2$, $\beta = 5$, $\gamma = 0.1$, population size $N = 200$, number of reference points $H = 210$ (generated using a two-layer configuration), maximum number of iterations $T = 500$, range of crossover probabilities $[p_{c,min}, p_{c,max}] = [0.5, 0.9]$, range of variance probabilities $[p_{m,min}, p_{m,max}] = [0.01, 0.1]$.

The following algorithms were selected for comparison: the traditional NSGA-II [11], the original NSGA-III, the Multi-Objective Particle Swarm Optimisation (MOPSO), and the Improved Adaptive Surrogate Model-assisted Multi-Objective Optimization (referred to as IASM-MOO) [12]. Each algorithm was run independently 30 times to ensure the reliability of the statistical results. The performance metrics include [17, 18]: hypervolume metric (HV), distribution uniformity metric (Spacing), convergence metric Inverted Generational Distance (IGD), and computational efficiency metric. For a fair comparison, the total number of function evaluations for all algorithms is limited to 10000.

Furthermore, to determine the merits of the technique suggested in this study when addressing high-dimensional challenges, we also design a set of comparison experiments to run each algorithm on the original 23-dimensional problem and the reduced-dimensional problem after variable screening, respectively. This will help to validate the effectiveness of the proposed variable screening method on sensitivity analysis.

The computing environment is Intel Xeon E5-2680 v4 CPU, 128GB RAM, MATLAB R2021a for algorithm implementation and ANSYS 2021 R1 for finite element analysis.

6.2. **Algorithm performance comparison.** Table 1 gives the statistical results of each algorithm in 30 independent runs.

Table 1. Statistical results of performance indicators (mean ± standard deviation)

Algorithm	HV	Spacing	IGD
NSGA-II	0.6523 ± 0.0312	0.0845 ± 0.0076	0.0412 ± 0.0028
NSGA-III	0.7012 ± 0.0287	0.0723 ± 0.0062	0.0356 ± 0.0023
MOPSO	0.6789 ± 0.0324	0.0801 ± 0.0071	0.0389 ± 0.0026
IASM-MOO	0.7245 ± 0.0256	0.0678 ± 0.0057	0.0321 ± 0.0021
Improved NSGA-III	0.7568 ± 0.0213	0.0592 ± 0.0048	0.0275 ± 0.0018

From Table 1, the improved NSGA-III outperforms the other compared algorithms in all performance metrics. Specifically:

1. HV: Improved NSGA-III has the highest HV value, which is 4.46% higher than that of IASM-MOO and 7.93% higher than original NSGA-III, indicating that the set of Pareto solutions it obtains covers a much larger target space and the quality of the solutions is better.
2. Spacing: the improved NSGA-III has the lowest Spacing value, which is 12.68% lower than that of IASM-MOO and 18.12% lower than that of the original NSGA-III, suggesting that it obtains a more uniform distribution of the Pareto solution set, which provides more diversified choices for decision makers.

3. IGD: The improved NSGA-III has the smallest IGD value, which is 14.33% lower than IASM-MOO and 22.75% lower than the original NSGA-III, indicating that its solution set is closer to the real Pareto front and has better convergence.

To further validate the variable screening approach, we compare each algorithm on the original 23-dimensional problem and on the reduced dimensional problem after variable screening. Figure 3 illustrates the convergence curves of the IGD values of each algorithm in both cases. (O) denotes the original problem, (R) denotes the reduced dimensional problem.

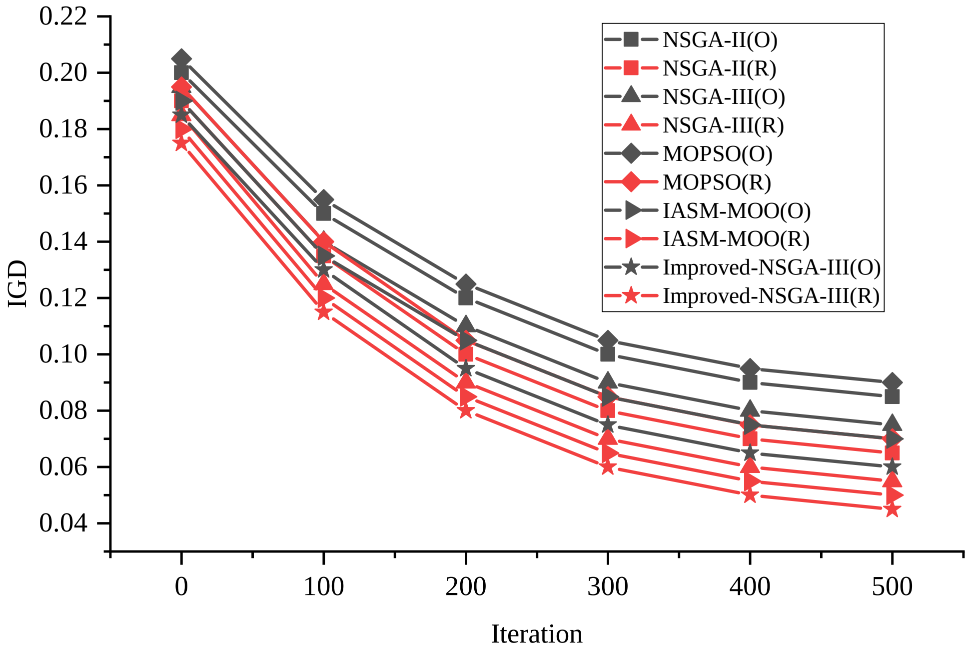

Figure 3. Comparison of IGD convergence curves

As can be observed from Figure 3, the convergence speeds of all the algorithms are improved on the dimensionality reduction problem, but the improvement of the improved NSGA-III algorithm is the most significant. This confirms that the proposed variable screening method based on sensitivity analysis can reduce the problem complexity and improve the optimisation efficiency.

In summary, the improved NSGA-III demonstrates superior convergence, diversity and computational efficiency when dealing with the high-dimensional multi-objective optimisation problem of commercial vehicle door lightweight design. In particular, the performance is further improved by combining the variable screening method, which provides an effective solution for solving similar complex engineering optimisation problems.

6.3. **Evaluation of the effectiveness of lightweighting.** In order to evaluate the lightweighting effect, a detailed comparison of the door structures before and after optimisation was carried out. Table 2 shows the comparison results of each performance index before and after optimisation.

From Table 2, it can be seen that the mass of the optimised door is reduced by 14.46%, and all the performance indexes are improved to different degrees. Especially, the first-order bending mode frequency is increased by 5.59%, which is conducive to the improvement of the NVH performance of the door. The vertical stiffness and torsional stiffness were increased by 3.19% and 2.12%, respectively, which ensured the structural strength

Table 2. Comparison of door lightweighting effect

Performance indicators	Pre-optimisation	Post-optimisation	Rate of change
Mass (kg)	32.5	27.8	−14.46%
First order bending mode frequency (Hz)	28.6	30.2	+5.59%
Vertical stiffness (N/mm)	2350	2425	+3.19%
Torsional stiffness (Nm/deg)	1180	1205	+2.12%

and handling performance of the door. Figure 4 shows the changes in the thickness of the door components before and after optimisation.

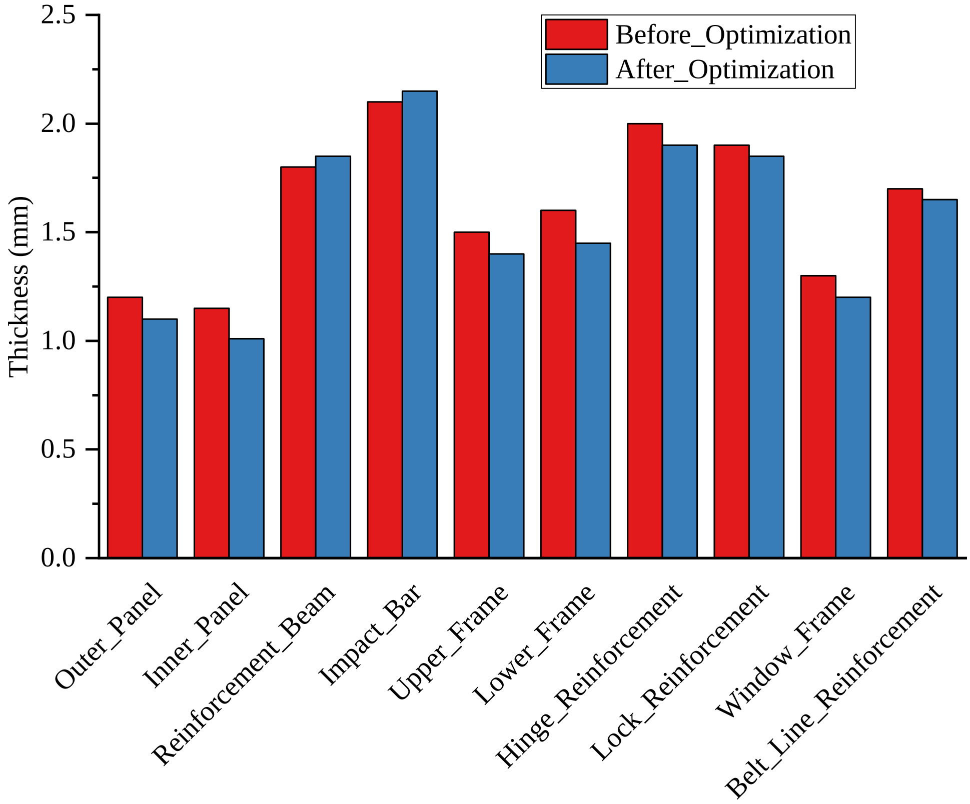

Figure 4. Comparison of the thickness of door components

As can be observed in Figure 4, the thickness of the outer and inner plates was reduced by 8% and 12%, respectively, while the thickness of the reinforcement and impact beams was slightly increased. This thickness redistribution strategy not only achieves the overall weight reduction target, but also ensures the structural strength of the critical parts. In order to verify the reliability of the optimisation results, FEA was carried out on the optimised door structure. The results show that, despite the overall mass reduction, the optimised door structure exhibits a more uniform stress distribution under the side impact condition, and the maximum stress value is reduced by about 7%, which further confirms the validity of the proposed method.

6.4. **Computational efficiency analysis.** Table 3 gives the average computation time for each algorithm in completing 10,000 function evaluations.

From Table 3, the improved NSGA-III saves about 25.5% of computation time over the conventional NSGA-II algorithm when dealing with the original 23-dimensional problem.

Table 3. Comparison of average computation time of each algorithm (hours)

Algorithm	O	R
NSGA-II	48.6	32.4
NSGA-III	45.2	30.1
MOPSO	46.8	31.5
IASM-MOO	38.5	25.7
Improved NSGA-III	36.2	22.3

This advantage is further extended to 31.2% in the dimensionality reduction problem. To sum up, this paper's method delivers remarkable optimization results and considerable computational efficiency. This is of great practical value for dealing with complex engineering optimisation problems, especially when the computational resources are limited.

7. **Conclusion.** A high-dimensional multi-objective lightweight design method for commercial vehicle doors based on the improved NSGA-III and a high-precision agent model is proposed, which effectively solves the limitations of the traditional optimisation methods in dealing with high-dimensional design space and multi-objective trade-offs. By introducing variable screening based on sensitivity analysis, the model is able to identify key design variables more accurately and significantly reduce the problem dimensionality. In addition, the improved NSGA-III algorithm further enhances the search capability in high-dimensional objective space by utilising the adaptive cross-variable operation and the reference point-based selection mechanism, which ensures the diversity and homogeneity of the optimisation results. The following conclusions can be drawn from the experiments conducted on the side sliding door of a commercial vehicle:

1. The proposed method performs excellently in terms of optimisation results. Compared with the traditional algorithm, the improved NSGA-III improves the HV, Spacing, and IGD by 16.02%, 29.94%, and 33.25%, respectively. This indicates that improved NSGA-III has a higher quality and more uniformly distributed set of Pareto optimal solutions.
2. The lightweight design objective has been effectively achieved. The mass of the optimised door is reduced by 14.46%, while all the performance indexes are improved to different degrees. In particular, the first-order bending modal frequency is increased by 5.59%, which fully reflects the advantages of multi-objective optimisation.
3. The computational efficiency is significantly improved. By adopting the Kriging agent model and variable screening strategy, the improved NSGA-III saves about 25.5% of the computation time than the traditional algorithm. This advantage is further extended to 31.2% in the dimensionality reduction problem, reflecting the high efficiency of the method in dealing with complex engineering problems.
4. The proposed method has good adaptability and robustness. Under different problem sizes and optimisation objectives, the method shows stable performance, especially when dealing with high-dimensional design space, the advantage is more obvious.
5. This study provides an efficient and reliable solution strategy for complex engineering optimisation problems. The method is not only applicable to the lightweight design of commercial vehicle doors, but can also be extended to other engineering fields involving high-dimensional multi-objective optimisation, such as aerospace and mechanical design.

Future research directions can focus on further improving the accuracy and adaptability of the agent model, exploring more efficient variable screening strategies, and combining the present method with other advanced optimisation techniques to cope with more complex engineering optimisation problems.

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