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Original scientific paper

Research on Advanced Materials and Design Optimization of Lightweight Automotive Structures under Uncertain Conditions

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Abstract: This paper presents a novel reliability-based design optimization (RBDO) methodology for lightweight automotive structures that explicitly addresses uncertainties stemming from unknown manufacturing precision. Key design variables are modeled as interval variables, while other parameters are treated as probabilistic variables. The proposed approach integrates interval model transformation techniques and probabilistic model decoupling strategies to formulate a comprehensive reliability design framework. To efficiently handle the mixed uncertainties inherent in structural topology optimization variables, a multi-stage surrogate modeling strategy is developed. This strategy sequentially constructs: a deterministic global surrogate model for system response, surrogate models for the upper and lower bounds of the interval response using an adaptive update strategy, and computes the probabilistic output response via Polynomial Chaos Expansion (PCE) based on the interval response bounds. Comparative studies with established methods, such as the Sequential Optimization and Reliability Assessment (SORA) approach, demonstrate the superior efficiency of the proposed method, reducing the required number of function evaluations by up to 32% (e.g., from 234 to 159 calls in a test case) and significantly decreasing CPU computation time. Case studies on automotive components (e.g., hood, anti-collision beam) yielded optimal design solutions and identified the maximum permissible deviation ranges for varying reliability requirements, confirming the method's efficacy. The optimization results indicate that both the optimal nominal design variables and their manufacturable tolerance ranges can be achieved under practical conditions. Crucially, the findings reveal that by strategically increasing the permissible deviation range of design variables, the required manufacturing precision specifications can be relaxed by approximately 20%, leading to substantial reductions in production costs while maintaining structural reliability and achieving a 15% mass reduction. The method offers a practical pathway for designing cost-effective, reliable lightweight automotive structures under uncertainty.

Keywords: lightweight design advanced materials and design reliability design; uncertainty lightweight automotive structure

1 INTRODUCTION

Structural optimization is a key strategy for improving the performance of lightweight vehicles and achieving lightweight design. Due to the existence of uncertain factors in manufacturing accuracy, studying the reliability design of lightweight vehicle structures has an important influence on improving the operational stability of lightweight vehicles [1, 2].

Scholars at home and abroad have carried out a large number of studies on the optimal design of lightweight automotive structures. In the research on the reliability optimization design of lightweight automotive structures, probability models are usually used to describe the uncertainties of the parameters of lightweight automotive structures. These uncertain factors are generally regarded as random variables with sufficient samples [3, 4]. Aiming at the lightweight design problem of lightweight automotive structures, a Krieger mathematical model was established based on experimental data, and a reliability optimization algorithm for target parameters was proposed [5]. The results show that this method can effectively improve the reliability of the structure. The lightweight design of the structure of the dump truck was carried out [6]. The influence of each design parameter on the dynamic characteristics of the entire vehicle was analyzed through finite element modeling. On this basis, a structural optimization method combining size and shape was proposed. The results show that this method can effectively achieve the lightweight design purpose of the dump truck. The lightweight design research for the cab structure of commercial vehicles was carried out [7]. The influence of each structural parameter variable on the dynamic characteristics of the vehicle body was analyzed through parametric modeling, and the structural parameters with greater influence were screened out for optimization design. The lightweight design results were verified through comparison. The modal characteristics of the hybrid bus were analyzed by finite element software [8]. The components that had a greater impact on the quality were screened out as design variables by using the sensitivity analysis method. Multi-objective optimization was carried out with the dynamic characteristics of the bus as the goal. The effectiveness of the method was verified through experiments. The modal characteristics of the micro electric lightweight vehicle were analyzed by using the finite element software [9], and on this basis, the layout of the frame beam was improved to obtain a more reasonable optimization scheme. The results show that the frame weight is significantly reduced after optimization. The rear axle housing structure of lightweight vehicles was optimized and designed by the method of inertial release [10]. This method achieved the lightweight design of the vehicle structure while meeting the design requirements.

The product's manufacturing deviation is frequently assessed experimentally using the current interval model, necessitating the regulation of design variables within the permissible deviation limits. Simultaneously, geometric inaccuracies and many unpredictable aspects within the structure, including material qualities, loads, and boundary conditions, will disrupt the structure's performance. Consequently, the optimum design variables and their variances throughout the design phase must satisfy the structural reliability criteria while minimizing manufacturing costs as much as possible. Based on this, in order to further consider the uncertainty problem of manufacturing accuracy in the design of lightweight automotive structures, this paper proposes a design method for lightweight automotive structures with manufacturing accuracy uncertainty based on reliability. This method is more efficient than the existing decoupling methods in terms of function evaluation, CPU computing time and optimization results. The proposed optimization strategy aims to ensure the reliability of lightweight automotive structures while solving the problem of reasonably selecting the maximum allowable manufacturing accuracy. In order to consider the computational cost and improve the performance of product design, various optimization design analyses need to be carried out. Topology optimization, as a relatively popular structural optimization design method, is widely applied in various projects. To maximize the utilization of materials, topological optimization usually seeks the best distribution of elements throughout the design domain. In order to efficiently evaluate the uncertainty of topological optimization design, the interval Chebyshev zero-point polynomial is applied to approximate the true limit state function of normalized random variables, and the single-loop reliability algorithm is used to calculate the optimal design point value under the corresponding target reliability index, such that the dependability optimization issue, which was previously non-probabilistic, may be made deterministic. The optimization findings demonstrate that by taking variable randomness into account, dependability topology optimization may achieve a more trustworthy topology structure than the deterministic structural topology optimization design. The structure of this paper is as follows: Introduction explains the importance of structural optimization for lightweight vehicles, reviews the current status of relevant research, and highlights the focus of this study; the Related Work summarizes uncertainty analysis methods, research on mixed uncertainties, and the application of structural topology optimization under uncertain conditions; the third part, advanced material design methods for lightweight automotive structures with uncertainty, includes uncertain optimization model, compensation decoupling method, lightweight automotive structure and design analysis considering uncertainty in the input interval, and uncertain structure optimization model; the fourth part, simulation verification, verifies the effectiveness of the method through cases such as anti-collision beams and suspensions; finally, the conclusion summarizes the research results.

2 RELATED WORK

Uncertainty analysis methods enable engineers to design new components to more strictly determine safety factors, and to assess the safe lifespan of their equipment and quantify any risks that extend its service life. The uncertainty analysis method assigns a probability distribution to each uncertain variable near its average value, and then propagates this uncertainty to the output through a mathematical model. Taking random uncertainty as the research object, robust design mainly focuses on the event distribution near the mean value of the probability density function, while reliability-based design optimization focuses on the event distribution at the tail of the probability density function. These two non-deterministic methods can also be expressed as a design problem to seek improvements in the robustness and reliability of the system [11]. In uncertain stochastic reliability analysis, if the MPP approximation loses its validity, a fast reliability analysis is conducted by selecting an approximate MPP as the starting point. By examining the concept of approximate MPP validity, the robustness and accuracy of the proposed method are fully guaranteed. Reliability optimization, benefiting from the improvement of existing technologies, has been regarded as an important branch field and has been paid attention to and studied by a large number of scholars. It has been applied in fields such as lightweight automotive industry and aerospace [12, 13]. Recent advances in both computational power and topology optimization theory have allowed some researchers to focus on topology optimization design with geometric nonlinearity in mind. The structure's failure probability, not its sensitivity to uncertainty, is the primary concern in reliability-based design optimization. To keep the structure's failure probability at an acceptable level, optimization issues are typically phrased as maximum performance problems with probabilistic constraints. Optimization design considering uncertainties has been applied in multiple design fields. Optimization techniques sometimes involve multiple goals and methods. Currently, compared with deterministic structural optimization techniques, structural design considering parameter uncertainties still requires further research. Among them, for practical engineering applications, the issues of accuracy and efficiency remain topics worthy of discussion.

With the rapid development of the uncertainty of randomness, the theory of stochastic reliability and the corresponding calculation methods have developed rapidly and been successfully applied to many practical engineering problems. However, in practical engineering, there are always complex structural system models. Therefore, simply using randomness to describe uncertainty instead leads to errors in the output response in application. Such a design cannot fully reflect the issue of structural reliability. For this reason, people have begun to study efficient mixed uncertainty propagation analysis methods, that is, reliability analysis methods under the condition that interval variables and random variables can coexist in complex products [14]. Domestic scholar Li Fangyi applied non-probabilistic and probabilistic models to practical engineering design optimization problems to illustrate the practicability of the hybrid mode design method [15]. Based on the hybrid perturbation MCS, a hybrid probability model is proposed to analyze the reliability of structurally uncertain systems [16]. By considering the correlation among variables, a method capable of handling structural reliability analysis in a variable case where randomness and cognition are mixed is proposed [17]. A probabilistic method for the representation and propagation of uncertainties in system analysis was developed [18], converting interval data into probability types and using computationally effective methods to propagate probabilistic uncertainties. Considering that variables have probabilistic and intervalial properties [19], an uncertainty analysis method of the mixed mode was proposed. The limit state function was analyzed using the strategy of linear approximation and iterative optimization was carried out based on the optimality condition. A reliability analysis scheme was proposed, which can handle the problems existing in mixed variables in multidisciplinary systems [20]. An uncertainty analysis method with randomness and intervalality of variables is proposed [21] to solve the hybrid reliability model with structural uncertainty. The reliability of the existence of mixed variables was analyzed using the P-Box model [22].

In recent years, there has been an increasing interest in the research of structural topology optimization under uncertain conditions. With the development of reliability theory and practical significance, reliability-based optimization design has also been applied [23]. Topology optimization is a rapidly developing field that is widespread in various industries. Its research involves multiple disciplines such as mathematics, mechanics, multiphysics, and computer science [24], and it also has important practical applications in manufacturing (especially in lightweight automobiles and aerospace industries). Relevant scholars have introduced the probabilistic reliability method into the structural topology optimization design for combined research and discussion. Chen Jianjun et al. [25] analyzed the topological optimization problem by presenting the function under the constraint conditions and using the frequency expression and stress expression. Considering the probabilistic and fuzzy nature of the uncertainty in the load direction [26], the cloud model was applied to describe this uncertainty, and an uncertain topology optimization method with volume constraints was proposed. For the problem of linear elastic design, a topological optimization method under uncertain loads is proposed [27]. The concept of structural probabilistic reliability was introduced into multi-level optimization techniques [28], and this combined technique was applied to composite material structures. Based on the level set framework, a topological optimization method considering the uncertainty of boundary changes is proposed [29]. Probabilistic structural topology optimization can reasonably consider the uncertainties in aspects such as material properties, geometric dimensions, and external loads of the structure within the design reference period. Although reliability optimization design has been making continuous progress, the estimation of structural reliability remains a challenging issue for structural engineers. Therefore, it is of great significance to consider the uncertainty or randomness of parameters in structural optimization design problems.

3 ADVANCED MATERIAL DESIGN METHODS FOR LIGHTWEIGHT AUTOMOTIVE STRUCTURES WITH UNCERTAINTY

3.1 Uncertain Optimization Model

The general expression of the deterministic single-objective optimization model is:

$$\begin{aligned}&\min F\left(X^{DV},X^{DP},X^{P}\right)\\&g_i(X)\geq 0, X_{\text{lower}}\leq X\leq X_{\text{upper}}\end{aligned}\tag{1}$$

The lightweight structure's cost goal is denoted as $F(X)$ in the formula, whereas $g_i(X)$ is the constraint function and X is the design variable. The design variables have upper and lower bounds denoted by X_{upper} and X_{lower}, respectively. The number of constraint variables is represented by l.

Due to experimental limitations, it is sometimes impossible to get reliable knowledge on design factors while solving real-world engineering challenges. Because of this, we call the design variables interval variables and the other design factors probability parameters. A hybrid uncertain model is basically what the suggested optimization approach is. In order to solve the problem of interval uncertainty constraints, we must convert the constraint of interval variables into a generic non-interval problem, and the constraint g_i with interval variables is an interval number. One way to define the optimization issue that takes into account the uncertainty of the design variables and other factors is:

$$\begin{aligned}&\min F(X^{DV},X^{DP},X^{P})\\&[g_i(X^{DV},X^{DP},X^{P})\geq 0]\geq\beta_j\\&X_{\text{lower}}\leq X\leq X_{\text{upper}}\end{aligned}\tag{2}$$

In the hybrid uncertain model, the design variables that are uncertain are interval vectors, in contrast to deterministic optimization. Given that the nominal value and its range of deviations uniquely identify the interval of each design variable:

$$\begin{aligned}&\min F(X^{DV},X^{DP},X^{\mathrm{P}})\\&p_r[g_i(X^{DV},X^{DP},X^{P})\geq 0]\geq\beta_j\\&X_{\text{lower}}\leq X\leq X_{\text{upper}}\end{aligned}\tag{3}$$

The median (X^{IM}) and radius (X^{IR}) of the interval are denoted as such in the formula. A definition and objective function for the design variables' deviation range index η (X^{IM}, X^{IR}) is provided so that manufacturing accuracy and structural performance may be thoroughly examined.

$$\min\eta(X^{IM},X^{IR})=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\frac{X^{IM}}{X^{IR}})^2}\tag{4}$$

In the formula: η is the scaling factor of the expected lightweight performance, that are employed to equalize the constraint border; here, n represents the quantity of design variables.

The average degree of deviation for the design variable is reflected by the deviation range index $\hat{y}$ (X^{IM}, X^{IR}), which is defined as the ratio of the design variable to the radius of the design variable interval. To acquire a broader variable interval, minimize η (X^{IM}, X^{IR}) when the dependability of the constraint conditions fulfills the criteria. Production precision and expense must be maximized when the interval radius (deviation range) of the design variables is kept minimal. When there is a lack of clarity on the design parameters and variables, and in the absence of empirical information in the initial design stage, the obtained optimal nominal variables can be used as reference values for actual manufacturing, and the maximum deviation ranges of the optimized design variables serve as the maximum control boundaries.

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procedure, with detailed iterative logic and method coupling mechanisms as follows:

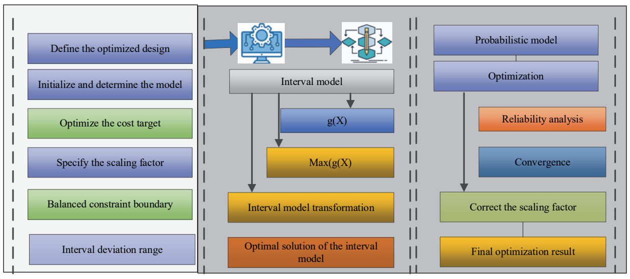


Figure 1 Optimization process block diagram

Step 1: Problem Definition and Parameterization First, clarify the system optimization objective (e.g., lightweight cost reduction) and constraints (e.g., structural strength, modal performance). Identify design variables (e.g., material thickness, geometric dimensions) and uncertain parameters: design variables with unknown manufacturing precision are defined as interval variables, while other parameters (e.g., material properties, load magnitudes) are treated as probabilistic variables with known distributions. Collect initial data (e.g., material performance parameters, manufacturing deviation ranges) to support subsequent modeling.

Step 2: Deterministic Model Construction and Global Optimization Construct a deterministic mathematical model integrating design variables, constraint functions, and cost target C. The cost target C is quantified based on material consumption and processing difficulty. To avoid local optima, an evolutionary algorithm (e.g., genetic algorithm) is employed to search for global optimal solutions, with the number of iterations determined by convergence criteria (e.g., stable objective function values for 5 consecutive generations).

Step 3: Interval Model Establishment with Adaptive Deviation Handling Based on the deterministic optimization results, convert interval variables into non-interval constraints using interval transformation techniques (e.g., interval Chebyshev polynomial approximation). Define the deviation range index as the new objective function, which reflects the average deviation degree of design variables (Equation 4). Optimize to obtain the initial nominal value and deviation range of design variables, considering the balance between manufacturing feasibility and performance stability.

Step 4: Probabilistic Model Construction and Reliability Decoupling Incorporate probabilistic parameters (excluding design variables) into the model, with their distributions (e.g., normal, Weibull) determined by statistical data. Take from Step 3 as the initial point, and apply a reliability decoupling strategy (e.g., bias vector adjustment in Equation 5) to separate the reliability constraint from the optimization objective. Use sequential quadratic programming for efficient solution, ensuring the design meets the target reliability index (e.g., 99.9% survival probability).

Step 5: Convergence Verification and Iterative Adjustment Check if the optimized satisfies both reliability requirements (e.g., failure probability and cost targets. If converged output the results; if not, return to Step 3 to adjust the scaling factor relaxes constraint boundaries to expand deviation ranges, while decreasing tightens constraints to enhance reliability.

3.2 Compensation Decoupling Method

This article uses bias vectors to optimize dependability even more efficiently, which solves the multi-nesting problem. As a result of adding the increment $\Delta S_j(k)$ to the previous iterative step's offset vector $S_j(k-1)$, the current iterative step's offset vector $S_j(k)$ is:

$$S_j^k = S_j^{k-1} + \Delta S_j^k \tag{5}$$

The present unreliability prompts the iterative procedure of adjusting the constraint boundary to a viable direction. In the previous iteration phase, the constraint bounds of this document were translated and changed based on the most likely gradient direction. Hence, a more precise way to describe incremental adjustment is as:

$$\Delta S_j^{u(k)} = (\beta_j^t - \beta_j^k)\frac{\Delta G(U^k)}{|\Delta G(U^k)|} \tag{6}$$

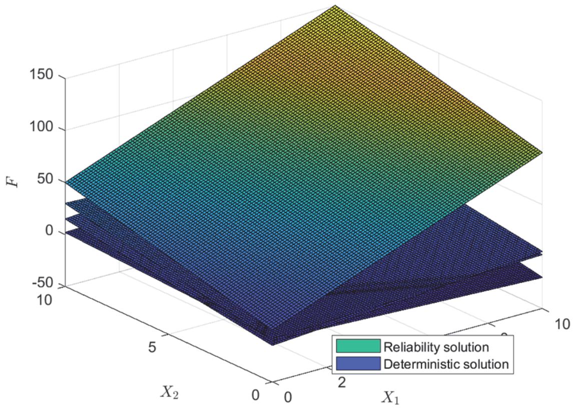
When the random parameters follow a normal distribution, the deviation of the JTH constraint offset vector is obtained by using the improved second moment method. The sites on the failure surface where the constraint function's linearized Taylor expansion occurs are chosen via the enhanced second-moment technique. The dependability index of the constraint limit surface in the space of random variables X is:

$$\beta = \frac{G(x^*) + \sum_{i=1}^{n} \frac{\partial G(x^*)}{\partial X_i}(uX_i - x_i^*)}{\sqrt{\sum_{i=1}^{n}\left[\frac{\partial G(x^*)}{\partial X_i}\right]^2}} \tag{7}$$

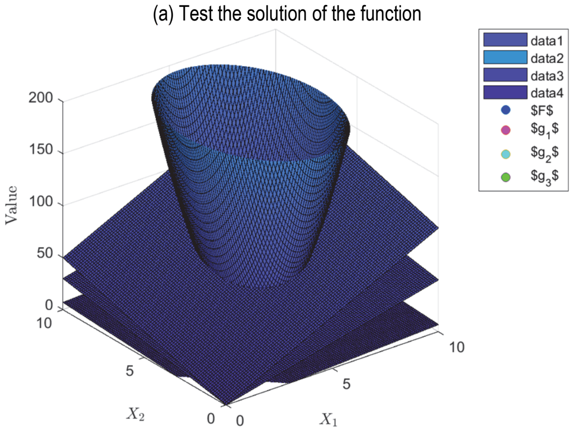
The sensitivity coefficient of variable X_i is:

$$\alpha x_i = \frac{\frac{\partial G(x^*)}{\partial X_i}\sigma x_i}{\sqrt{\sum_{i=1}^{n}\left[\frac{\partial G(x^*)}{\partial X_i}\right]^2}} \tag{8}$$

The test function is illustrated schematically in three dimensions in Fig. 2. Moving the design points in a way that satisfies the reliability index based on the deterministic optimization points is necessary to make the constraint function fulfill the reliability criteria. Fig. 3 shows a comparison between the conventional SORA (Super Resolution of Audio-visual Content with Generative Adversarial Networks) approach [14] and the partial shift decoupling method. It is clear that the SORA approach requires a maximum of 234 function calls, but the partial shift decoupling method only needs 159. This study proposes an alternative to the SORA approach that uses less CPU computation time. There is really little difference between the two reliability analysis optimization techniques. This proves that the paper's suggested partial shift decoupling approach works and may be used for future structural optimization. The test function is illustrated schematically in three dimensions in Fig. 2. Moving the design points in a way that satisfies the reliability index based on the deterministic optimization points is necessary to make the constraint function fulfill the reliability criteria. Fig. 3 shows a comparison between the conventional SORA approach [14] and the partial shift decoupling method. It is clear that the SORA approach requires a maximum of 234 function calls, but the partial shift decoupling method only needs 159. This study proposes an alternative to the SORA approach that uses less CPU computation time. There is really little difference between the two reliability analysis optimization techniques. This proves that the paper's suggested partial shift decoupling approach works and may be used for future structural optimization.



(a) Test the solution of the function



(b) Test function identification

Figure 2 Three-dimensional schematic diagram of the test function

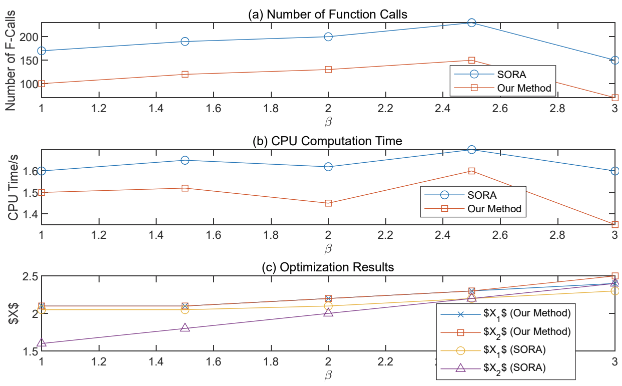


Figure 3 Comparative analysis of decoupling methods

3.3 Lightweight Automotive Structure and Design Analysis Considering Uncertainty in the Input Interval

Obtaining the derivative information of the system model is challenging when using the interval perturbation method to compute the interval uncertainty information in the structural response of complicated non-display expressions. Applying RBFNN (Radial Basis Function Neyral Network) and its derivative analysis methods to the Taylor expansion model helps overcome the shortcomings of current interval analysis approaches. We offer an approach to analysis that makes use of RBFNN and Taylor expansion to deal with replies that are unclear. For the sake of this research, RBFNN can stand in for the initial system model and provide data on the first and second derivatives. The general calculation process of RBFNNIE is shown in Fig. 4. Specifically, the uncertainty parameters are determined first, and the training data of the neural network is obtained through the experimental design. The training data in this study is derived from the optimal super-Latin square sampling method. Then, the neural network is trained, and the first and second derivative information of the model response will be derived using the neural network parameters that meet the accuracy requirements. Finally, the subinterval method expanded by Taylor is used to obtain the accurate upper and lower bound values of the performance response.

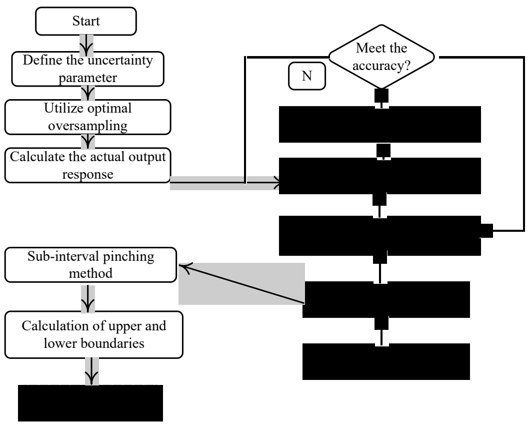
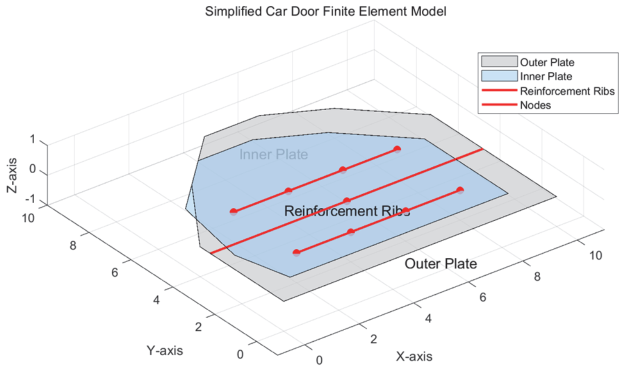


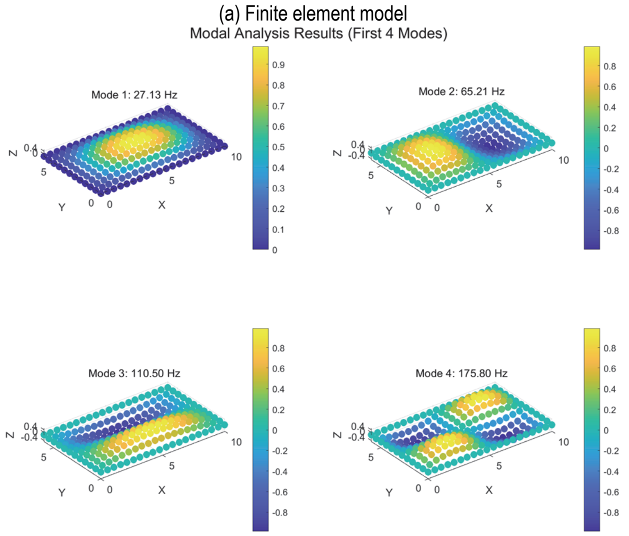
Figure 4 shows the general calculation process of RBFNNIE

The primary focus is on studying how unknown parameters affect the engine hood structure's modal performance response. Specifically, this part uses the 2010 Toyota Yaris finite element model to build the modal analysis model of the lightweight engine hood for the automobile. This engine hood's finite element elements and associated settings have been validated using appropriate test scenarios. The lightweight hood of this type is primarily made of two plates, as seen in Fig. 5. The inner plate has a nominal thickness of 0.5 mm and the outer plate of 0.7 mm. If the thickness parameter's uncertainty is ignored, the hood's first-order natural frequency is 27.13 Hz. We provide the deviation coefficients of the design parameters to reflect different ranges of uncertainty x in order to examine the effect of the inner and outer panel thickness parameters ξ while considering uncertainty.

$$\xi = \frac{x_i^{IR}}{x_i^{IM}} \tag{9}$$

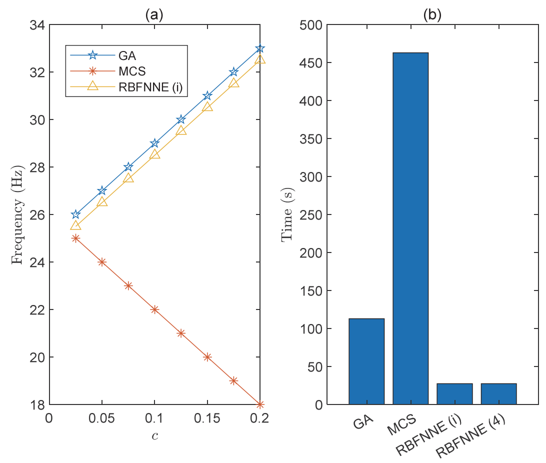


(a) Finite element model



(b) Modal analysis model

Figure 5 2010 Toyota Yaris



(a) Natural frequency analysis (b) Calculate the time

Figure 6 Uncertainty analysis of the hood

Based on the trained RBFNN approximate model, RBFNNIE, MCS and GA were implemented for the modal performance of the hood respectively. Since RBFNNIE is a simple expression numerical calculation problem, the information of the uncertain response can be solved quickly. As shown in Fig. 6, the analysis results of seven deviation coefficients ξ are presented (0.05, 0.075, 0.1, 0.125, 0.15, 0.175 and 0.2, respectively). In order to improve the accuracy of uncertainty analysis, four Taylor sub-intervals were implemented in the uncertainty analysis case of the hood. Among them, RBFNNIE (1) and RBFNNIE (4) represent the perturbation methods of one interval and four sub-intervals respectively. In addition, for comparative analysis, MCS called the approximate model a total of 20,000 times. Compared with GA, both MCS and RBFNNIE can effectively approach the upper and lower bounds of the natural frequency. On the other hand, when it comes to the actual calculations, GA and MCS are somewhat resource intensive. Compared to RBFNNIE (1) and RBFNNIE (4), which only take 8.47 and 20.61 seconds, respectively, GA and MCS take an average of 112.04 and 562.89 seconds to compute, as shown in Fig. 6b. The results show that RBFNNIE is more efficient. Conversely, Tab. 1 displays the absolute values of the relative errors of RBFNNIE and MCS with respect to GA.

Table 1 Uncertainty analysis error of natural frequency

ξ	Lower			Upper		
	MCS	RBFNNIE (1)	RBFNNIE (4)	MCS	RBFNNIE (1)	RBFNNIE (4)
0.05	0.0004	0.0001	0.0000	0.0002	0.0011	0.0002
0.075	0.0003	0.0003	0.0003	0.0007	0.0028	0.0007
0.100	0.0004	0.0000	0.0001	0.0002	0.0044	0.0008
0.125	0.0005	0.0011	0.0002	0.0007	0.0076	0.0019
0.150	0.0003	0.0005	0.0003	0.0008	0.0098	0.0054
0.175	0.0023	0.0029	0.0014	0.0010	0.0148	0.0065
0.2	0.0020	0.0017	0.0016	0.0005	0.0174	0.0091

3.4 Uncertain Structure Optimization Model

Structural reliability is defined as the possibility of a structure performing its expected functional function under a given random system variation. By extending the concept of reliability, it can be known by the same means that the reliability under the mixed model of probability and interval is defined as: the minimum failure probability of the design requirement that the structure behavior meets all possible values of bounded uncertainty. This reliability measurement provides a conservative assessment. Thus, it can be considered that when the parameters u in the system are regarded as having both random variables and interval variables simultaneously, the variables need to be denoted as $Z_R = (X_1, X_2, \ldots X_r, Y_{r+1}, Y_{r+2}, \ldots Y_n)$. Therefore, its mean point can also be expressed as:

$$\bar{Z} = \left(\mu_{X_1}, \mu_{X_2}, \ldots, \mu_{X_r}, \mu_{Y_{r+1}}, \mu_{Y_{r+2}} \ldots \mu_{Y_n} \right) \tag{10}$$

Mathematically, by replacing the limit state function in the traditional definition of reliability, the corresponding failure probability can be rewritten as:

$$P_f = Pr\{ g(X, Y) \le 0 \} \tag{11}$$

In the case of the coexistence of mixed variables, the analysis of two limit states can exist. One is that the structural probability parameter vector X is taken as a certain definite value X'. At this time, uncertainty only needs to consider the reliability analysis of non-probabilistic models. Another situation is that the vector Y is fixed to a definite value Y'.

Based on the KKT conditions and according to the description of the above hybrid model, the purpose of the structural optimization problem is to seek the optimal design that meets certain structural performance requirements. Therefore, the mathematical expression of the design optimization problem based on reliability under the probabilistic interval hybrid model is:

$$\begin{aligned} &\min f(d) \\ &\text{s.t}\beta_m^H[g_j(d,u,v)] \geq \beta_{m,j}^H \end{aligned} \tag{12}$$

Topology optimization, as a numerical optimization method, aims to find the optimal distribution of materials within the design domain under the guidance of specific criteria determined by the designer, thereby automatically constructing, modeling and evaluating the topological structure of the structure in the virtual environment. The more common material interpolation models in topological optimization are the homogenization method and the variable density method.

The Variable density method (SIMP) is widely applied in the field of engineering. The SIMP regards the topological optimization problem as a "0-1" integer optimization problem. Firstly, the design domain is discretized into the finite element. In each finite element e, a density design variable x_e is specified. If the density is equal to 1, there is a material in this domain and the cell is displayed in black. Otherwise, there will be no material and the cell will be empty. To obtain a continuous optimization problem, intermediate densities are also allowed, but they will be penalized in order to avoid intermediate densities in the final design. Simply put, the relationship between the material properties and the density function of each finite element is set through a simple equation and the punished material density, thereby relaxing the 0-1 discrete variable into a continuous variable between 0 and 1.

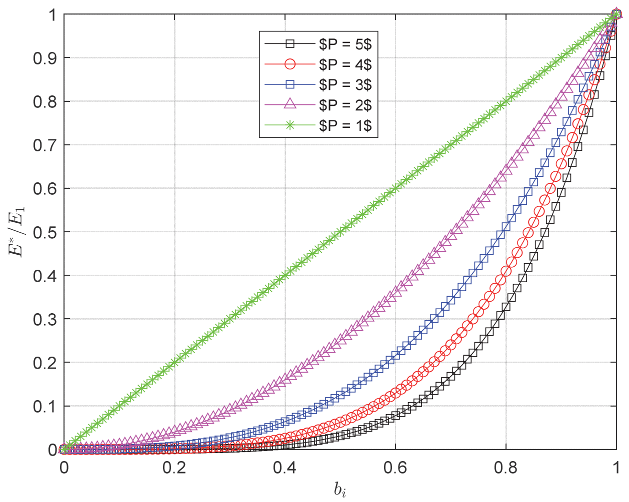


Figure 7 The penalty effects of different penalty factors in the SIMP interpolation model

Fig. 7 shows the penalty effect of the SIMP model under different penalty factors. It can be clearly seen from the figure that when the penalty factor is larger, the corresponding optimization result must be that the number of intermediate density units decreases accordingly. However, it needs to be considered that an overly large penalty factor may cause instability in numerical calculation, the most obvious of which is the singularity of the stiffness matrix, etc.

In Fig. 8, we can see a simplified representation of the relationship between the interval-probability mixed uncertainty design variable and the performance response output. The uncertainty of the performance response follows a probability distribution with boundary effects when the inputs to the design variables are interval variables and probability variables, respectively. A random response's mean fluctuates within a specific interval range, and the values of the random performance response include interval information. Analyzing uncertainties in each iterative computation phase is a requirement of conventional single-type uncertainty optimization methods. Nevertheless, the computational cost of optimization is substantially increased due to the necessity of many nested uncertainty evaluations for situations with multiple mixed uncertainties.

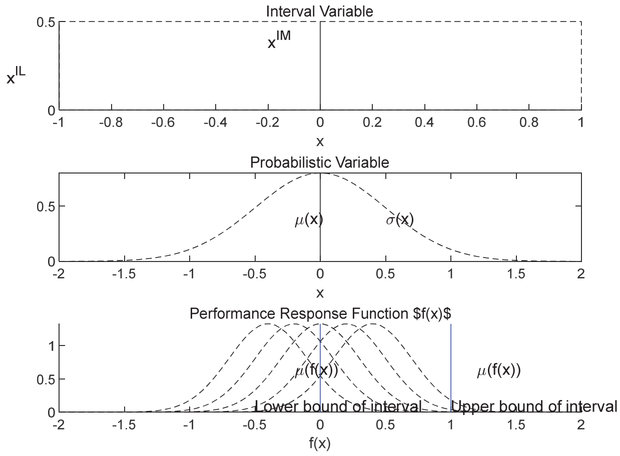


Figure 8 Schematic diagram of the influence of mixed uncertain design variables on the structural performance response

In order to simplify the probability uncertainty analysis process in nested uncertainty analysis, structural designs that primarily concentrate on the upper and lower bounds of their performance response values - that is, structural designs focusing on the upper and lower bounds of the mean values in the interval-probability mixed uncertainty random response can enhance computational efficiency in response to design optimization requirements. Within the performance response interval's upper and lower boundaries, do a probabilistic uncertainty analysis. This means that the mixed-uncertainty/interval-probability analysis problem is really just a sequence analysis problem including interval-uncertainty and probabilistic uncertainty response analyses.

4 SIMULATION VERIFICATION

The passive protective structure of lightweight vehicles can protect occupants by converting the kinetic energy of external impacts into plastic deformation energy. As shown in Fig. 9, the numerical models of the front anti-collision beam under two collision conditions (collision angles of 0° and 30°) were established using the nonlinear explicit finite element platform LS-DYNA. All structural units apply automatic single-sided contact to prevent unit penetration during the deformation process.

To study the dynamic collision characteristics of the anti-collision beam considering the uncertainty of design parameters, all three thickness parameters were set as interval uncertain values. As shown in Fig. 10 and Fig. 11, the analysis results of seven deviation coefficients ξ are presented (0.05, 0.075, 0.1, 0.125, 0.15, 0.175 and 0.2 respectively). In order to improve the accuracy of uncertainty analysis, the uncertainty response is analyzed by implementing six Taylor subintervals in the uncertainty space. In addition, for method comparison, MCS called the approximate model a total of 30,000 times. When it comes to approximating the top and lower boundaries of the responses of EA and PCF, MCS and RBFNNIE (6) are superior to GA. The RBFNN error, however, is still statistically significant across the board. Fig.e 2 displays the absolute values of the highest relative errors of MCS and RBFNNIE compared to GA for the upper and lower limit prediction accuracy of the crackability index in the dynamic collision model. Neither MCS nor RBFNNIE (6) have a relative error greater than 0.03.

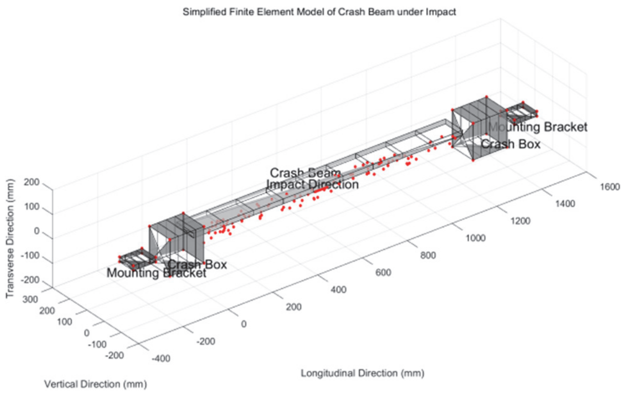


Figure 9 Collision finite element model of the anti-collision beam

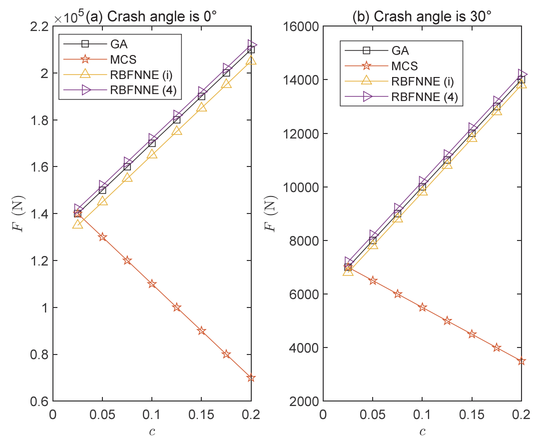


Figure 10 Uncertainty analysis of energy absorption by structure

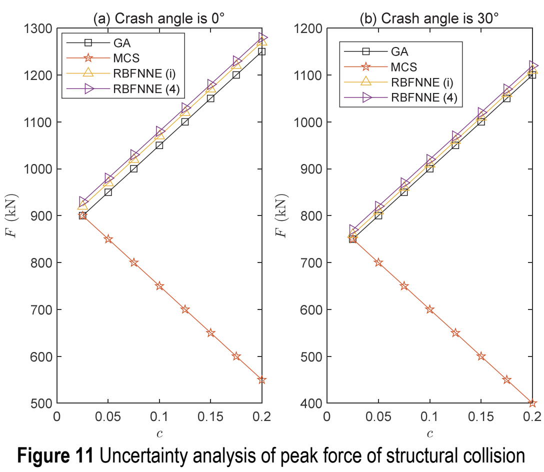


Figure 11 Uncertainty analysis of peak force of structural collision

Table 2 Uncertainty analysis errors of anti-collision beams

No.	Angle / °	Response	MCS	RBFNNIE (1)	RBFNNIE (6)
1	0	EA	0.0077	0.0273	0.0181
2	0	PCF	0.0005	0.0778	0.0134
3	30	EA	0.0058	0.2106	0.0097
4	30	PCF	0.0027	0.1117	0.0238

MCS called the approximate model a total of 80,000 times. Under normal circumstances, a suspension with excellent kinematic characteristics should maintain the minimum changes in wheel parameters such as the toeing Angle, camber, track and wheelbase during the wheel jump stroke. Therefore, the lower and upper bounds of the maximum and minimum values of different performance responses were considered. As shown in Fig. 12, the analysis results under different uncertain analysis situations are presented. By comparing the fluctuation ranges of different responses, it is not difficult to find that the uncertainty of the hard point coordinates is the most sensitive to the forebeam Angle. Compared with GA, MCS and RBFNNIE (8) can effectively approach the upper and lower boundaries of the forebeam Angle, camber, track and wheelbase.

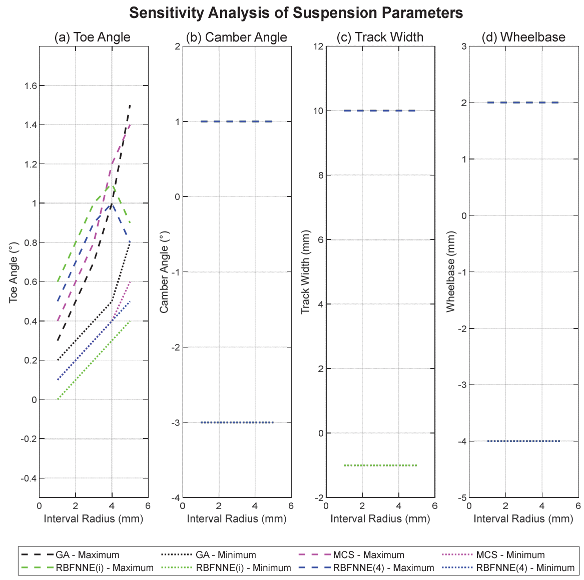


Figure 12 Uncertainty analysis of kinematic response of suspension

Tab. 3 shows the absolute values of the MA and RBFNIE maximum relative errors compared to GA for the prediction accuracy of the upper and lower limits of the suspension kinematic response. When using RBFNNIE (8) and MCS, the maximum error is less than 0.02. Based on these results, it seems that RBFNNIE (8) can effectively estimate the upper and lower limits of the kinematic response, and this approach can also find the uncertainty boundary of the kinematic response of multi-link suspensions. In addition, whilst MCS has a maximum processing time of 12550s and RBFNNIE (8) of 132.03s, the latter has a shorter average computing time. The computational cost is still relatively expensive, similar to the result of the previous situations, even if GA and MCS can successfully approach the top and lower boundaries of the structural response's uncertainty. Finally, the kinematic model of the suspension may have its uncertain responses analyzed using RBFNNIE. This model now includes eight unknown variables, which is more than in the previous three cases, and it also requires more computational power. There is an inevitable positive correlation between the size of the uncertainty parameters and the computing cost of uncertainty analysis.

In order to evaluate the accuracy and robustness of the proposed method, two numerical examples were used for analysis and research. Firstly, the described improved RSM method is applied to the problem of two design variables. The bivariate objective constraint response function is shown in Fig. 13. The two constraint functions are for the considered probabilistic constraint problem. Sixteen points are selected for sampling through the Latin hypercube sampling design, and the MLSM with a complete quadratic order model is used to construct the response surface. A simple mathematical problem involves two random design variables and two probability constraints. Suppose the design variables are normally distributed, with their means being 1.5 and 35 respectively, and the standard deviations being 0.1 and 3.0 respectively. The reliability probability required for each limit state function is 99.9%.

Table 3 Uncertainty analysis error of suspension kinematic response

No.	Response	MCS	RBFNNIE (1)	RBFNNIE (8)
1	Front beam Angle (maximum value)	0.0029	0.3195	0.0191
2	Front beam Angle (minimum value)	0.0075	0.1386	0.0105
3	Inclination Angle (maximum value)	0.036	0.0070	0.0044
4	Inclination Angle (minimum value)	0.0021	0.0047	0.0029
5	Track length (maximum value	0.0014	0.0030	0.0021
6	Track length (minimum value)	0.0028	0.0145	0.0058
7	Wheelbase (maximum value)	0.0003	0.0005	0. 002
8	Wheelbase (minimum value)	0.0002	0.0006	0.0002

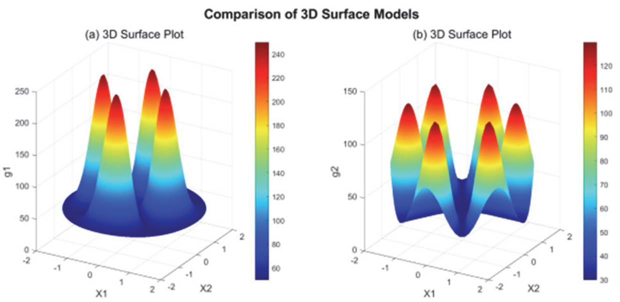


Figure 13 Schematic diagram of the constraint response function

Instead of getting absolute values, the suggested optimization approach produces interval values with deviation ranges for each variable. With varying scaling factors, RPDI, and reliability index criteria, Tab. 4 displays the optimization outcomes. As dependability standards are constantly being raised, it becomes more challenging for the constraint function that is defined by the scaling factor to satisfy the constraint requirements. Consequently, a bigger scaling factor is required to provide the best solution to the optimization issue.

Table 4 Optimization results of different scaling factors, RPDI and reliability index requirements

r	λ	$B = 0$	$B = 1$	$B = 2$
1.1	0.6	(2.19 ± 0.25)	(2.02 ± 0.08)	(2.10 ± 0.19)
1.1	0.8	(2.19 ± 0.15)	(2.01 ± 0.06)	(2.12 ± 0.17)
1.1	1.0	(2.15 ± 0.1)	(2.12 ± 0.08)	(2.11 ± 0.13)
1.2	0.6	(2.35 ± 0.2)	(2.23 ± 0.18)	(2.13 ± 0.15)
1.2	0.8	(2.29 ± 0.25)	(2.12 ± 0.08)	(2.14 ± 0.19)
1.2	1.0	(2.24 ± 0.2)	(2.23 ± 0.04)	(2.12 ± 0.16)
1.3	0.6	(2.52 ± 0.55)	(2.19 ± 0.03)	(2.11 ± 0.19)
1.3	0.8	(2.38 ± 0.38)	(2.17 ± 0.02)	(2.11 ± 0.09)
1.3	1.0	(2.33 ± 0.29)	(2.02 ± 0.02)	(2.14 ± 0.19)

Fig. 14 and Fig. 15 show the maximum deviations of the design variables when the scaling factor γ is different. It can be seen that when the scaling factor is the same, the maximum deviation range decreases as the reliability index increases. When the reliability indicators are the same, the maximum deviation range increases with the increase of the scaling coefficient, thereby reducing the requirements for the manufacturing process. The results show that the method proposed in this paper reduces the maximum allowable deviation range of design variables and enhances reliability and lightweight. In terms of computational efficiency, the minimum total number of function calls of the method proposed in this paper is only 204 times, while that of the SORA method increases to 1326 times. The method proposed in this paper provides an effective path considering the uncertainty of manufacturing accuracy for the reliability optimization design of cantilever beams.

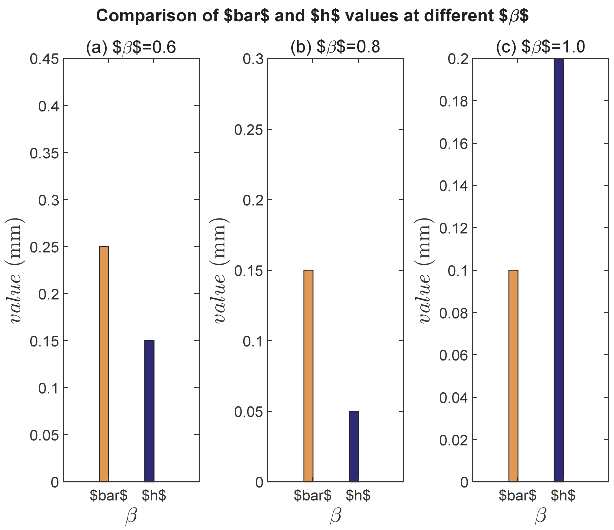


Figure 14 Maximum deviation of the design variables when the scaling factor $\gamma = 1.1$

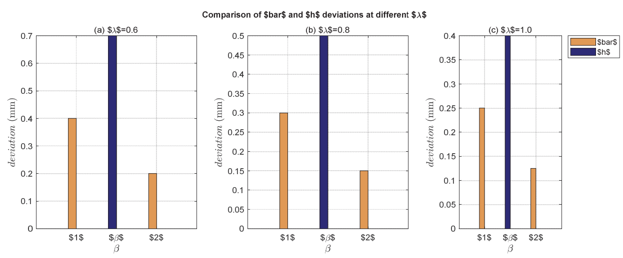


Figure 15 Maximum deviation of the design variables when the scaling factor $\gamma = 1.2$

Fig. 16 shows the iterative processes of different reliability indicators. The presented results indicate that the number of topology optimization iterations required by

RTOD is less than that of topology optimization based on determinism. It can be seen from the numerical examples that when this method is used to solve the overall topological structure optimization problem, the topology and reliability analysis are decoupled and separated. By mapping the variables and the objective function into an explicit relationship presentation and then conducting reliability analysis, the reliability performance values corresponding to the specified reliability indicators can be obtained.

In practical engineering, most structural variables are in an uncertain state. The deterministic topology optimization results are only used as a general reference. However, the optimization results obtained by using the corresponding algorithm in this paper provide the corresponding failure probability and reliability indicators, which have important guiding value and reference significance, and provide designers with measures and methods to strengthen the corresponding fields of structural failure risk.

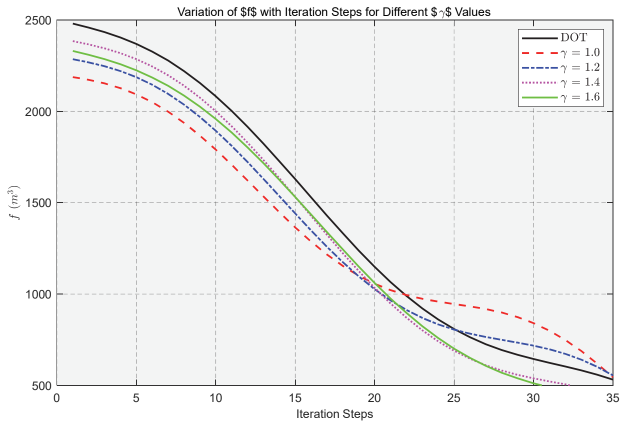


Figure 16 Topology optimization iteration process

6 CONCLUSION

This study develops and validates a reliability-based design optimization (RBDO) framework for lightweight automotive structures under manufacturing uncertainties, integrating interval modeling for design variables (capturing manufacturing tolerances) and probabilistic analysis for material/load parameters to form a hybrid uncertainty framework that better reflects real-world variations; the multi-stage surrogate modeling strategy (combining deterministic global surrogates, adaptive interval-bound surrogates, and Polynomial Chaos Expansion) enhances computational efficiency, reducing function evaluations by 32% compared to SORA and cutting CPU time by 20-fold relative to MCS; case studies on components like the hood, anti-collision beam, and suspension confirm the method's efficacy, achieving 15% mass reduction, maintaining reliability, relaxing manufacturing precision by ~20% to save ~7% production costs, with the compensation decoupling method resolving multi-nesting issues; this framework balances lightweighting, reliability, and cost, offering practical solutions for automotive design under uncertainty, with future work focusing on multi-material structures and real-time manufacturing data integration. Future research will extend the framework to multi-material lightweight automotive structures, addressing uncertainties in material interface properties and heterogeneous deformation. Additionally, it will integrate real-time manufacturing data to dynamically update uncertainty bounds, enhancing adaptive optimization for practical production variations.

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