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Optimal design of internal pressure-resistant square compartment based on strength analysis

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Abstract: [**Objectives**] For the design of a marine internal pressure-resistant square compartment that meets the design requirements of strength and lightweight, the neural network surrogate model is combined with heuristic intelligent optimization algorithms and applied to the shape and size optimization of the components of such a compartment. [**Methods**] The corner chamfer radius, plate thickness, and girder types are selected as design variables for conducting three-dimensional (3D) parametric modeling, and sample points are selected according to the optimal Latin hypercube experimental design method. The response values of these sample points are then calculated to build a surrogate model of the radial basis functions (RBF) neural network. To perform global optimization, the surrogate model is combined with three heuristic optimization algorithms separately, i.e., the adaptive simulated annealing (ASA) algorithm, multi-island genetic algorithm (MIGA), and particle swarm optimization (PSO) algorithm. [**Results**] The results show that the three hybrid optimization methods can all reduce structural weight on the basis of meeting the allowable strength requirements, and the optimal solution obtained by the RBF-ASA method in the overall situation has a good weight reduction effect. [**Conclusions**] This study can provide valuable references for the optimal design of internal pressure-resistant square compartment structures, and it is of great significance to overcome the key technical problems faced by ships using nuclear power plants.

Keywords: internal pressure-resistant square compartment; structure optimization; surrogate model; heuristic algorithm; parametric modeling

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0 Introduction

Compared with conventional icebreakers, nuclear-powered icebreakers have the advantages of higher endurance and stronger power. Therefore, the research on nuclear-powered ships is of great significance for China's polar strategy. The particularity of nuclear power plants puts forward higher requirements for the hull structure design. Compared with onshore nuclear power plants, ships require a higher space utilization rate, and thus a ship reactor compartment should be square, but this will cause the stress concentration issue in the corner of the compartment, which makes the tightness of the hull structure encounter great challenges. Unlike the reactor containment of onshore nuclear power plants, which are often made of concrete, the reactor compartment is still made of steel as part of the overall structure of a nuclear-powered ship. In an accident, the compartment will be subjected to a large uni-

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form internal pressure load and high temperature. Since the mechanical properties of steel are greatly different from those of concrete, the structure performance of the reactor compartment under this special load condition is not clear. Therefore, it is necessary to conduct in-depth research on the structure optimization design of the internal pressure-resistant square compartment.

In the methods for structure optimization design of ships, the optimization algorithms based on surrogate models and heuristic algorithms have gradually replaced the classical optimization algorithms, such as the criterion method and mathematical programming method. By the response surface model, LIU [1] optimized the design of the middle section of a container ship, which effectively reduces the weight of the structure. The back-propagation neural network surrogate model constructed by CHENG et al. [2] has high accuracy in simulating the pressure-resistant bulkhead of the submarine end. On the basis of this model, the genetic algorithm is used for optimization and achieves a good weight reduction effect. ZHUO[3] combined the surrogate model of the radial basis function (RBF) neural network with multiple optimization algorithms and achieved good results in the lightweight design of the overall compartment section of oil tankers.

Some progress has been made in research on the structure optimization of the internal pressure-resistant square compartment. Through the submodel technology and the shape and topology optimization technology, GAO et al. [4] found a new type of corner structure for a rectangular compartment with internal pressure, and the results showed that the stress concentration can be alleviated. CHEN et al. [5] adopted the genetic algorithm to optimize the platform position and support pillar layout of the internal pressure rectangular compartment, and the results showed that the bending stress of the grillage can be effectively reduced. CHEN et al. [6] optimized the support pillar layout and prestress of the rectangular compartment with internal pressure by the genetic algorithm, and the results showed that the maximum bending stress of the top deck could be further reduced. At present, the research on internal pressure-resistant square compartments is mainly focused on reducing local stress, and there is a lack of lightweight research on the basis of considering the stress level of the entire compartment. Most of the adopted optimization methods optimize the shape while ignoring the size optimization of components. Moreover, the optimization algorithms used are often single, and a comparative analysis of the optimization effects of various algorithms is absent.

In this paper, the structure of marine internal pressure-resistant square compartments is taken as the research object, and the idea of optimizing the design of the corner shape and the size of each component of the entire compartment is proposed. It is expected that the most lightweight structure design that satisfies the allowable stress can be obtained globally through the hybrid optimization method combining the surrogate model of the RBF neural network and multiple heuristic algorithms. In addition, the optimal algorithm is given through comparative analysis.

1 Structure optimization design for internal pressure-resistant square compartment

Firstly, on the basis of the design specifications of pressure-resistant hulls and nuclear power equipment, an internal pressure-resistant square hull structure was designed, and its structure performance was preliminarily evaluated through numerical simulation. Then, a three-dimensional (3D) parametric model was built on the basis of size and shape optimization. Next, sample points were screened by the experimental design method, and the true response values under the sample points were calculated by the parametric model. Finally, the direction of local optimization was preliminarily determined through sensitivity analysis, and then global optimization was conducted by combining the surrogate model of the RBF neural network and optimization algorithms, so as to obtain the most lightweight structural design scheme that meets the strength requirements. The flowchart of the structure optimization design of internal pressure-resistant square compartments is shown in Fig. 1.

1.1 Material selection method for internal pressure-resistant square hull

The commonly used materials for pressure-resistant hulls include steel, aluminum alloy, titanium alloy, composite material, and fiberglass-reinforced plastic (FRP). Among them, steel, as the most economical and most well-studied material in various aspects, is still the first choice for marine reactor compartments. Considering that the inner hull

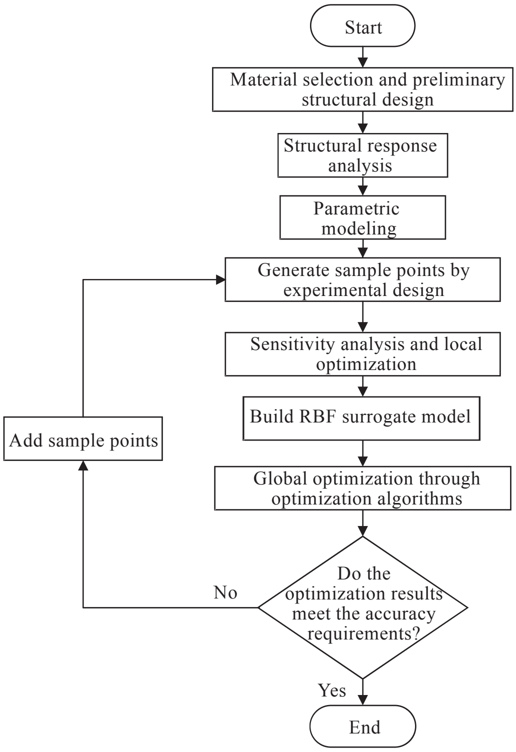


Fig.1 Flowchart of optimal design

is directly subjected to high temperature and internal pressure, the steel used is 921A steel with great high-temperature resistance, and the outer hull and the strengthening structure between the inner and outer hulls are made of DH40 high-strength steel. In the design, with the consideration of the influence of high temperature on the properties of steel, the mechanical properties of steel at high temperature are calculated according to the ANSI/ AISC 360-05 [7] specifications, and the elastic modulus is reduced with 400 ℃ as the reference temperature. According to *Rules for Classification of Diving Systems and Submersibles* issued by China Classification Society (CCS) [8], the allowable structural stress takes the minimum value by the following equation:

$$[\sigma] = \frac{R_{\mathrm{m}}}{2.7}, \quad [\sigma] = \frac{R_{\mathrm{eH}}}{1.5} \tag{1}$$

where R_{m} is the tensile strength of the material, N/mm^2; R_{eH} is the yield strength of the material, N/mm^2.

The properties of 921A and DH40 steel are shown in Table 1.

Table 1 Parameters of steel properties

Property parameters	921A steel	DH40 steel
R_{m}/(N·mm^{-2})	655	510
R_{eH}/(N·mm^{-2})	590	390
$\left(\frac{R_{\mathrm{m}}}{2.7}\right)$/(N·mm^{-2})	243	189
$\left(\frac{R_{\mathrm{eH}}}{1.5}\right)$/(N·mm^{-2})	393	260
Elastic modulus E/(N·mm^{-2})	2.1×10^5	2.1×10^5
Density /(kg·m^{-3})	7 850	7 850
Allowable stress/MPa	243	189
Reduced elastic modulus/(N·mm^{-2})	1.4×10^5	1.4×10^5

1.2 Experimental design method

The selection of sample points in the experimental scheme is related to the accuracy and efficiency of the surrogate model, and each sample point in this paper represents a structural component combination method. Through scientific experimental design, the distribution of sample points selected in the experimental scheme can be more uniform and representative. Common experimental design methods include the orthogonal array, center combination design, Latin hypercube design, and optimal Latin hypercube design. Among them, the Latin hypercube design can fit high-order nonlinear relations and has a more effective space-filling capacity and higher efficiency than the full factorial design [9]. The optimal Latin hypercube design improves the inhomogeneity of the random Latin hypercube design and can effectively avoid the possibility of losing some design space regions [10]. Therefore, the optimal Latin hypercube method is selected for experimental design in this paper.

1.3 Principle of sensitivity analysis

For the intuitive reflection of the influence trend of each variable on the objective function, the value of the input variable is normalized to [−1, 1], and the least squared method is used to fit the sample points to obtain the linear regression response model. Then, the coefficient C_i in the model is converted into the percentage contribution N_i, as shown in Eq. (2), where N_i of the variable that has a positive effect on the objective function (as the variable value increases, the objective function will also increase) is positive, while N_i of the variable that has a negative effect on the objective function (as the value of the variable increases, the objective function decreases) is negative. A larger absolute value of N_i represents a higher influence of the corresponding variable on the objective function. Thus, the optimization direction of each variable can be preliminarily determined.

$$N_i = \frac{100C_i}{\sum_i |C_i|} \tag{2}$$

where i is the variable number.

1.4 Principle of surrogate model and common heuristic optimization algorithms

Considering the interaction of components, a surrogate model is used to replace the finite element model structure to improve the efficiency of structural optimization. Common surrogate models include the response surface model, neural network model, Chebyshev orthogonal polynomial model, and Kriging model. Compared with other surrogate models, the neural network model has a stronger ability to approximate complex nonlinear functions and is more suitable for fitting the response function of the complex compartment structure. The surrogate model of the RBF neural network was proposed by Moody and Darken [11] according to the local regulation and overlapping response principle of the cerebral cortex. It is actually a mapping function obtained by weighted linear superposition of multiple RBFs, with a three-layer forward network structure. Thereinto, the first layer is the input layer that accepts input variables. The input layer is mapped to the hidden layer through RBFs, and the hidden layer is mapped to the output layer through linear weighting. In this way, the output variables are obtained. The process of constructing the surrogate model of the RBF neural network is the process of obtaining the corresponding linear weighting coefficient matrix [12].

After the surrogate model is obtained, error analysis can be carried out on the constructed surrogate model of the RBF neural network by cross-validation. The goodness of fit can be measured by R-squared, the determinant coefficient in statistics, which ranges from 0 to 1. A larger R-squared indicates a better fitting degree.

Engineering optimization problems often have complex features such as nonlinearity and discontinuity, and traditional gradient optimization and direct search cannot find the global optimization solution. Therefore, for local optimization, researchers have simulated the physical annealing process, biological evolution mechanism, and algorithm of predation behavior of birds and employed global optimization algorithms [13-15] such as the adaptive simulated annealing (ASA), multi-island genetic algorithm (MIGA), and particle swarm optimization (PSO) algorithm. Instead of using the "single point" search for local optimization, these global optimization methods rely on the internal information exchange of the "group" and the intergenerational inheritance of the "group", namely, using global information for optimization. In addition, the above global optimization algorithms will add random operations to avoid the phenomenon of "precocity" (falling into local area search prematurely), such as "temperature jumps" in ASA, "mutation" in MIGA, and "random number enhancement" in the particle direction in PSO, and hence these algorithms can quickly converge to the global optimal point.

2 Example calculation

2.1 Preliminary structural design of the internal pressure-resistant square compartment

As a barrier to prevent internal gas from escaping, the internal pressure-resistant square compartment needs to effectively protect the internal facilities during an external accident. Therefore, it is appropriate to adopt the double-layer grid structure with better shielding and structural strength, as shown in Fig. 2 (the numerical unit in the figure: mm). Considering the serious stress concentration caused by structural discontinuity at the corners of the rectangular hull, the inner hull at the joint between the bulkhead and the top or bottom is modified into a rounded corner connection mode, and the curvature of the toggle plate under the rounded inner hull is consistent with the rounded corner of the inner hull. According to engineering experience, the sharp corners of the toggle plate are removed at 3/4 of the toggle plate height. For a smooth transition, the inner hull corner where three sides meet is in a 3D rounded shape composed of 1/8 spheres. The internal pressure-resistant square compartment is symmetrical on the left and right. In modeling

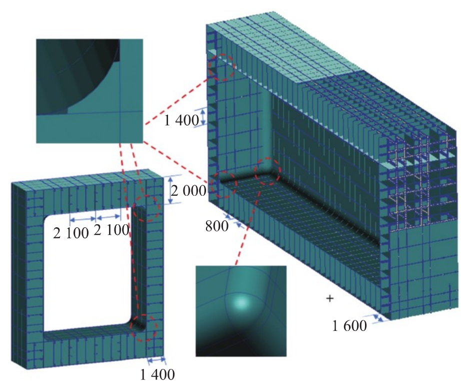


Fig.2 Geometric model

and finite element analysis, the entire square compartment structure is involved, but only half of the model is shown in the figure to clearly show the internal structure.

The entire internal pressure-resistant square compartment is composed of inner wall panels, outer wall panels, stiffened bulkheads between the inner and outer wall panels, and T profiles on the coaming panels. The space formed by inner walls has a size of 25.6 m × 8.4 m × 9.8 m. Between the inner and outer walls of each rib position, a circle of stiffened bulkheads is set along the rib position, and the rib spacing is set as 800 mm. Starting from the inner bottom plate of the double bottom, a circle of horizontal bulkheads is provided for every 1 400 mm rise in the vertical direction. In the ship width direction, a circle of longitudinal bulkheads is provided at every 2 100 mm interval. The distance between the inner and outer walls of the top and bottom is 2 000 mm, the distance between the inner and outer walls of the side is 1 400 mm; the distance between the inner and outer walls of the head and tail is 1 600 mm. The initial values and distribution positions of each component are shown in Table 2 and Fig. 3, respectively. In the figure, r represents the corner chamfer radius.

Table 2 Initial design value of components

Name of component properties	Initial design value/mm	Name of component properties	Initial design value/mm
Corner chamfer radius r of inner hull	600	Inner-hull bottom girder g_1	$\perp\frac{16\times 200}{20\times 100}$
Thickness of inner hull plate-1(corner) t_1	32	Inner-hull side girder g_2	$\perp\frac{16\times 200}{20\times 100}$
Thickness of inner hull plate-2(bottom) t_2	32	Inner-hull top girder g_3	$\perp\frac{16\times 200}{20\times 100}$
Thickness of inner hull plate-3 t_3	32	Inner-hull transverse bulkhead girder g_4	$\perp\frac{16\times 200}{20\times 100}$
Thickness of outer hull plate-1(corner) t_4	28	Outer-hull bottom girder g_5	HP220×11
Thickness of outer hull plate-2(bottom) t_5	24	Outer-hull side girder g_6	$\perp\frac{16\times 200}{20\times 100}$
Thickness of outer hull plate-3 t_6	20	Outer-hull top girder g_7	$\perp\frac{16\times 200}{20\times 100}$
Thickness of corner bulkhead t_7	26	Outer-hull transverse bulkhead girder g_8	$\perp\frac{16\times 200}{20\times 100}$
Thickness of horizontal bulkhead t_8	24	Bottom stiffener g_9	16×180
Thickness of longitudinal bulkhead-1(bottom) t_9	18	Side stiffeners g_{10}	16×180
Thickness of longitudinal bulkhead-2 t_{10}	20	Top stiffener g_{11}	16×180
Thickness of transverse bulkhead-1(bottom) t_{11}	24	Horizontal stiffener of transverse bulkhead g_{12}	16×180
Thickness of transverse bulkhead-2 t_{12}	22	Vertical stiffener of transverse bulkhead g_{13}	16×180
Toggle plate thickness t_{13}	20		

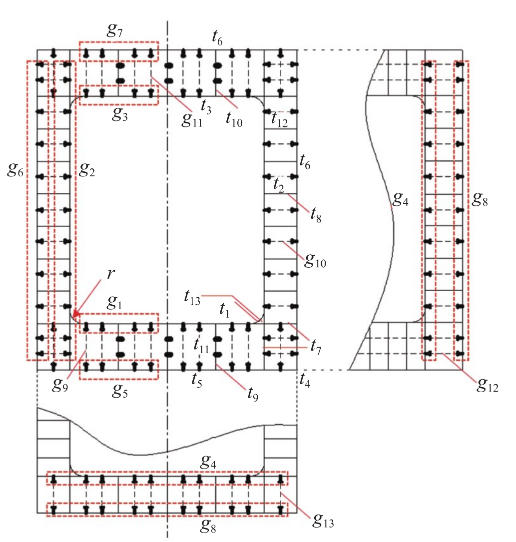
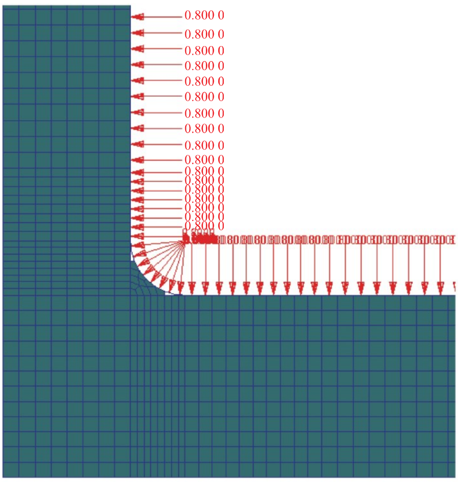


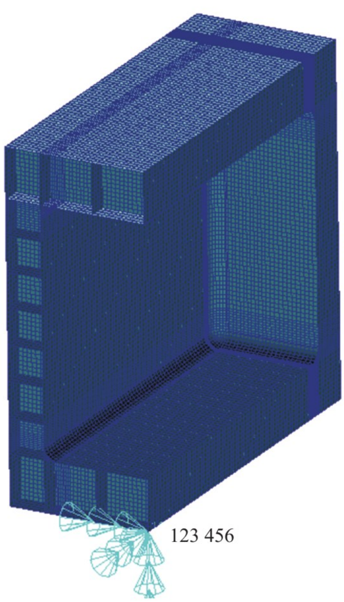
Fig. 3 Location of components

2.2 Structural response analysis under internal pressure conditions

In this paper, the finite element model of the pressure-resistant square compartment is built by MSC. Patran software. All plates adopt surface elements, and girders adopt beam elements. Thus, there are 314 720 elements and 251 416 nodes in total. The outer-hull plate elements are made of DH40 steel, and the other component elements are made of 921A steel. A uniform load of 0.8 MPa from inside to outside is arranged inside the inner hull, and the model under this load is in a self-balanced state. In addition, in this paper, only the response of the independent reactor compartment to the internal load is studied. Thus, only one node at the bottom center of the outer hull is taken to constrain six degrees of freedom (DOF), so as to limit the rigid-body displacement of the model, which is taken as the boundary condition. Fig. 4 shows how the loads and boundary conditions are applied to the model.



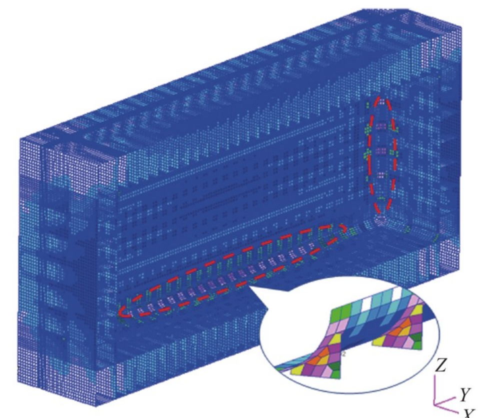
(a) Load application mode



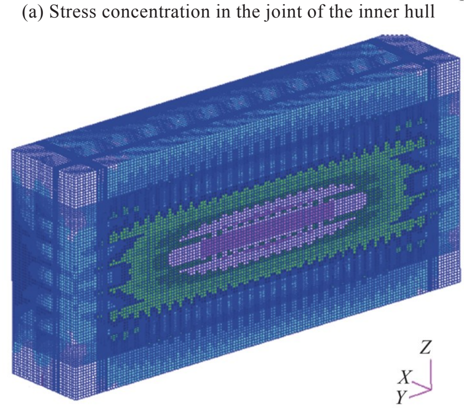
(b) Displacement constraint point

Fig. 4 Loads and boundary conditions of the model (1/4 scaled model)

The stress response of the model is calculated and analyzed, and the results are shown in Fig. 5. There is obvious stress concentration in the joint of transverse and longitudinal bulkheads of the inner hull as well as the joint between longitudinal bulkheads and inner bottom plates, while the stress response level of most other grillages is relatively low. Thus, there is a large design safety margin and a large optimization space. However, the plate element in the longitudinal middle part of the compartment, i.e., in the joint between the inner hull and the toggle plate, is the maximum stress point of the compartment, whose Mises stress reaches 237 MPa, close to the allowable stress value. As an important support structure, the overall stress response of the toggle plate is also at a high level. It is difficult to simultaneously reduce the weight of the component and ensure that the structure meets the allowable stress. Shape optimization should be considered to relieve stress concentration, and size optimization should be applied to reduce the weight of the component.



(a) Stress concentration in the joint of the inner hull



(b) Stress response of the outer hull

Fig.5 Stress response of internal pressure-resistant square compartment

2.3 3D parametric modeling

The 3D parametric modeling of the pressure-resistant hull was carried out by the Patran Command Language (PCL) and Patran software. In this way, we can study the influence of the corner chamfer shape of the pressure-resistant square hull and the size of each component on the strength and weight of the entire structure and thus obtain the optimal combination of each component. Since both shape and size optimization should be considered in the optimization work in this paper, meshing upon the steps from point to line and then to plane should be strictly followed during parametric modeling to avoid the dislocation of key component elements when the corner chamfer radius changes. Plate thickness, girder types, and corner chamfer radii at different positions were selected as design variables. 13 plate thickness variables from t_1 to t_{13}, 13 girder type variables from g_1 to g_{13}, and one shape variable (the corner chamfer radius r of the compartment) were set. Thereinto, the change of the girder variable is realized by selecting the girder number, namely that the available girders are arranged according to the minimum section modulus from small to large. In the section attribute library of Patran software, the beam attribute with a small section modulus corresponds to the number with a small value. When the variable is assigned to a certain number, the corresponding section characteristics will be assigned to the corresponding beam element. The location of each design variable is shown in Fig. 3.

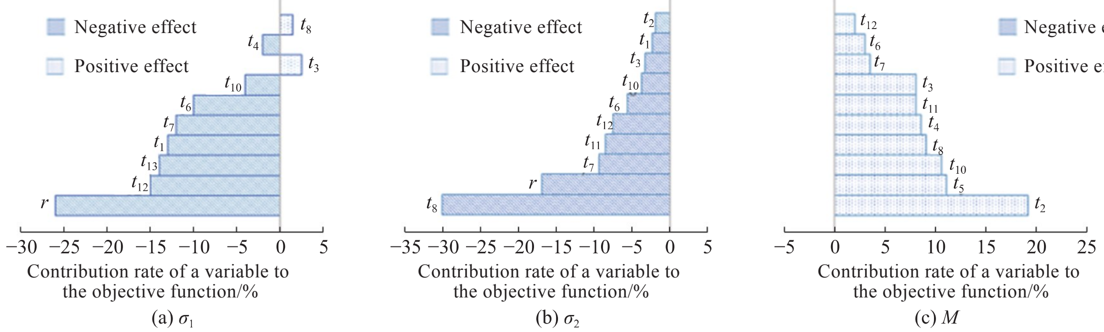


Fig.6 Effect of main variables that affect objective functions

2.4 Sensitivity analysis

Through the sensitivity analysis of each objective function, the optimization direction of each design variable is preliminarily predicted. The maximum Mises stress σ_1 of 921A steel structure, maximum Mises stress σ_2 of DH40 steel structure, and total weight M of the model were selected as three objective functions. The variables that greatly influence the three objective functions are shown in Figs. 6 (a)-(c), respectively. In the figure, the light-colored bar represents the positive effect, and the dark bar represents the negative effect. The variable with a small absolute value of the effect is not presented in the bar chart because it has little influence on the objective functions.

Regarding a single variable, the corner chamfer radius r has a significant effect on two objective stress values. Within the studied numerical variation range, a larger corner chamfer radius indicates a smaller objective stress value. The toggle plate thickness t_{13}, the transverse bulkhead-2 plate thickness t_{12}, the corner bulkhead plate thickness t_7, thickness t_6 of outer hull plate-3, and thickness t_1 of inner hull plate-1 (corner) have significant negative effects on stress and a relatively small contribution to mass, and thus proper thickening can be considered. Thickness t_{10} of longitudinal bulkhead-2, thickness t_8 of the horizontal bulkhead, thickness t_5 of outer hull plate-2 (bottom), thickness t_4 of outer hull plate-1 (corner), and thickness t_2 of inner hull plate-2 (bottom) demonstrate marginal negative effects on stress but a large contribution to mass, and thus they should be appropriately reduced. Other variables, such as girder size, have no obvious influence on the three objective functions and should be selected appropriately on the basis of the overall structure.

Sensitivity analysis can only qualitatively produce the general optimization direction, and for a complex overall structure like compartments, the interaction between different optimization variables is significant. Therefore, the selection of an independent variable optimization method for overall structure optimization may not be suitable, and global optimization algorithms should be adopted.

2.5 Surrogate model construction and global optimization

The design space is selected around the initial design point $\boldsymbol{X} = (r, t_1, t_2, ..., t_{13}, g_1, g_2, ..., g_{13})^{\mathrm{T}}$ as follows: the value range of each plate thickness variable is $(t_{i0} \pm 4)$ mm, with 2 mm as the step length of change. After sorting the girder types according to the section modulus, they are numbered in integers, and then the number is taken as the variable, with a range of $(g_{i0} \pm 1)$ mm. The value range of the shape variable (the corner chamfer radius r of the inner hull) is $(r_0 \pm 100)$ mm, with 50 mm as the step length. Using the optimal Latin hypercube experimental design method, 23 groups of sample points, 920 in total, were selected in the design space, which was divided into training sets and test sets to construct the surrogate model of the RBF neural network. For the reliability of the optimization results, the error difference between the response value of the final constructed surrogate model and the response value of the actual finite element model is required to be less than 5%. If the accuracy is insufficient, new sample points should be added from the test set to rebuild the surrogate model.

The error analysis of the constructed surrogate model of the RBF neural network was performed by cross-validation, and the results are shown in Table 3. As can be seen from the table, the R-squared values of the three objective functions are all above 0.92, which indicates the high reliability of the surrogate model.

Table 3 R-squared values of objective functions

Objective function	R-squared value
σ_1/MPa	0.959 33
σ_2/MPa	0.928 55
M/t	0.998 88

By this surrogate model, the optimization algorithms ASA, MIGA, and PSO were used for the global optimal solution. During the calculation, the optimization objects were 27 variables selected in the parametric modeling in Section 2.1, and the constraint condition was the maximum Mises stress of the two steel structures, which was less than the allowable stress in Table 1. The optimization objective was to minimize the total weight of the model. According to the problem description, the mathematical model for the structure optimization of the internal pressure-resistant square compartment is built as follows:

$$\begin{aligned} &\text{Find} \quad \boldsymbol{X}=(r,t_1,t_2,\cdots,t_{13},g_1,g_2,\cdots,g_{13})^{\mathrm{T}} \\ &\min \quad \sum M(\boldsymbol{X}) \\ &\text{s.t.} \quad \sigma_{i\max}(\boldsymbol{X}) \leqslant [\sigma_i];\ \ i=1,2 \end{aligned}$$

Upon optimization, the result is presented by the ratio of the optimized value of each variable to the initial value. The obtained results based on the above three optimization algorithms are shown in Fig.7. In the figure, the values above the initial value line indicate that the optimized value increases proportionately according to the ordinate; otherwise, it decreases.

For the complex structural response with multi-variables and multi-constraints, there may be an optimal solution set composed of multiple optimal solutions. Even by the same surrogate model, the opti-

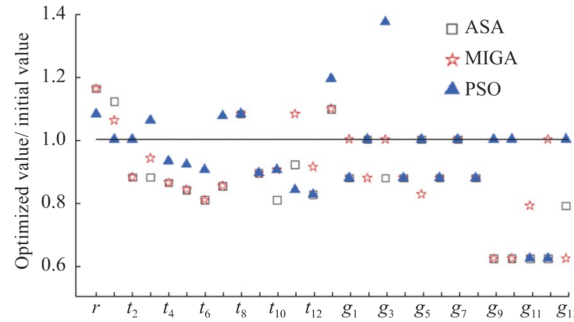


Fig. 7 Ratio of optimized values to initial values

mal solutions obtained by different optimization algorithms are not completely identical as an intelligent optimization algorithm itself has randomness and probability. Although it has the ability to find the global optimal solution, due to the limitation of time and parameter setting, it can only obtain a relatively good approximate optimal solution according to adaptive rules of the algorithm. Different adaptive rules may lead to different approximate optimal solutions, but they have the same overall characteristics toward the real optimal solution. However, how to improve the efficiency and quality of algorithm optimization remains to be further studied. The global optimization direction based on the surrogate model-optimization algorithms is not exactly the same as the local optimization direction obtained through sensitivity analysis. For example, under the above three global optimization algorithms, t_{12} and t_6 tend to be small, while t_8 is becoming larger, which is contrary to the direction of local optimization. The reason is that the multi-order interaction effect of each variable is considered in the global optimization method, which can better reflect the integrity of the internal pressure-resistant compartment structure.

The optimization schemes obtained by the three optimization algorithms were substituted into the finite element model for verification, and it was found that all of the maximum stress values met the requirements of allowable stress. The location was still in the joint between the inner hull and toggle plate in the middle section of the compartment, as shown in Fig. 7. The reduction effect of structural weight is significant, as shown in Table 4.

The optimization algorithms ASA, MIGA, and PSO can ensure the effective weight reduction of the model under the premise of satisfying the allowable stress. This is because each algorithm comprehensively considers the influence of component shape and size changes on structural properties.

Table 4 Results of structural response after global optimization

Objective function	Allowable value	Initial value	Optimized value of ASA	Optimized value of MIGA	Optimized value of PSO
σ_1/MPa	243	237.279	242.130	242.243	235.611
σ_2/MPa	189	178.761	187.103	185.818	180.756
M/t	–	1 569.780	1 355.172	1 445.334	1 422.096
Weight reduction percentage of model/%	–	–	13.67	7.93	9.41

Thus, the stress concentration of the structure can be alleviated under the action of shape optimization, and the unnecessary plate thickness can be reduced, or the size of the girder with a large section modulus can be reduced through size optimization. Eventually, the total weight of the compartment can be reduced. For the example in this paper, the compartment weight was reduced by 13.67%, 7.93%, and 9.41% by the three algorithms, respectively. The result based on the ASA optimization algorithm demonstrates a better weight reduction effect than that of the other two algorithms. To sum up, if the weight reduction optimization is carried out on the basis of the allowable structural stress constraint in a structure similar to internal pressure-resistant square compartments, the RBF-ASA hybrid optimization method is more likely to obtain good optimization results globally.

3 Conclusions

In this paper, parametric finite element modeling and strength evaluation are carried out for the internal pressure-resistant square compartment structure. Sensitivity analysis and the surrogate model-heuristic optimization algorithms are combined for optimization design research on the structure. The main conclusions are as follows:

1) The square compartment under internal pressure is prone to stress concentration in the joints of transverse and longitudinal bulkheads and inner bottom plates. Therefore, the arc-shaped inner hull corner plate with a proper radius and the toggle plate without sharp corners should be used as the connecting structure. When the maximum stress approaches the allowable stress, shape and size optimization of each component must be considered comprehensively to reduce the weight.

2) In the design space of this paper, the multi-order interaction effects of each variable are considered in the global optimization results based on the surrogate model-optimization algorithms, which can better reflect the integrity of the internal pressure-resistant compartment structure. Therefore, in contrast with the results of the sensitivity analysis method for independent variables, the optimization direction of component variables is not exactly the same, but they have the uniform overall characteristic of tending to the actual optimal solution. The corner chamfer radius of the inner hull and the thickness of the inner-hull plate and toggle plate at the corner should be appropriately increased, and the thickness of the longitudinal bulkhead and outer-hull plate should be appropriately reduced.

3) For the research object of this paper, the surrogate model of the RBF neural network has a high fitting accuracy, which can be combined with ASA, MIGA, and PSO separately to obtain an approximate optimal solution that meets the requirements of strength and lightweight in global optimization. Among them, the RBF-ASA optimization method is more likely to produce a good design scheme, which can provide a reference for the optimal design of internal pressure-resistant square compartment structure.

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基于强度分析的耐内压方形舱优化设计

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摘　要:[**目的**]为了使船用耐内压方形舱同时满足强度和轻量化的设计要求,将神经网络代理模型与多种启发式智能优化算法相结合,对耐内压方形舱室结构构件形状和尺寸进行优化分析。[**方法**]选取方形舱室角隅倒角半径、板材板厚、骨材型号等作为设计变量进行三维参数化建模,根据最优拉丁超立方试验设计方法选取样本点并计算响应值,从而构建径向基(RBF)神经网络代理模型。将该代理模型分别与自适应模拟退火算法(ASA)、多岛遗传算法(MIGA)和粒子群算法(PSO)这3种启发式优化算法相结合,进行全局寻优。[**结果**]结果显示,3种混合优化方法均能在满足许用强度要求的基础上减轻结构重量;RBF-ASA法在全局中寻求到的最优解具有相对较好的减重效果。[**结论**]所做研究可为耐内压方形舱室结构优化设计工作提供参考,对于攻克船舶运用核动力装置所面临的关键技术问题具有重要意义。

关键词:耐内压方形舱;结构优化;代理模型;启发式算法;参数化建模