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RESEARCH ARTICLE

Optimal Design of a Ship Multitasking Cabin Layout Based on the Interval Optimization Method

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Abstract
Searching for the optimal cabin layout plan is an effective way to improve the efficiency of the overall design and reduce a ship's operation costs. The multitasking states of a ship involve several statuses when facing different missions during a voyage, such as the status of the marine supply and emergency escape. The human flow and logistics between cabins will change as the state changes. An ideal cabin layout plan, which is directly impacted by the above-mentioned factors, can meet the different requirements of several statuses to a higher degree. Inevitable deviations exist in the quantification of human flow and logistics. Moreover, uncontrollability is present in the flow situation during actual operations. The coupling of these deviations and uncontrollability shows typical uncertainties, which must be considered in the design process. Thus, it is important to integrate the demands of the human flow and logistics in multiple states into an uncertainty parameter scheme. This research considers the uncertainties of adjacent and circulating strengths obtained after quantifying the human flow and logistics. Interval numbers are used to integrate them, a two-layer nested system of interval optimization is introduced, and different optimization algorithms are substituted for solving calculations. The comparison and analysis of the calculation results with deterministic optimization show that the conclusions obtained can provide feasible guidance for cabin layout scheme.

Keywords Cabin layout · Multitasking states · Uncertainty parameters · Interval optimization · Human flow and logistics

Article Highlights
- Ship cabin layout optimization design is conducted to find the optimal plan to improve the overall design efficiency.
- For multitasking states, the compatibility of the interval optimization method for different intensity requirements is analyzed.
- Uncertainty of adjacent strength and circulating strength are quantified by interval numbers.
- The applicability and superiority of interval optimization in the field of cabin layout design are revealed by a series of calculations.

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1 Introduction

The ship cabin layout has always been an important research issue in the field of ship design. With the rapid development of computers in recent years, the intelligent requirements for cabin layout design have also been increasing. Scholars have performed considerable research in this field.

Most cabin layout designs consider two-dimensional facility layout problems (FLPs). The FLP refers to minimizing the cost of material circulation between equipment by changing their locations. Drira et al. (2007) summarized the research conducted by some scholars and pointed out several research directions. Hani et al. (2020) proposed a new linear programming model in FLPs to optimize the width and number of passages and verify the effectiveness of the method through calculations. Shamsodin et al. (2021) proposed a new mathematical model for the dynamic FLP and solved the model by combining an improved genetic algorithm (GA) and cloud model-based simulated annealing (SA) algorithm. Compared with FLPs, the cabin layout problem has a more complicated system.

The cabin layout design refers to the reasonable determination of cabins' distribution positions between the superstructure and each deck of the main hull based on the specified performance indicators and requirements. Graph theory methods, heuristic algorithms, and system layout planning (SLP) methods are commonly used to solve such problems. Heuristic algorithms include the GA and particle swarm optimization algorithm. Among them, heuristic algorithms and SLP are more widely used in the marine field. Zhang (2015b) used SLP to optimize the layout of a ship meal system. Wang et al. (2018) applied an improved tabu search algorithm to optimize the design of ship cabins. In practical applications, combining several methods is effective. Hu et al. (2013) comprehensively applied SLP and GA to the layout design of ship cabins and established mathematical models for an optimal solution. Li et al. (2019) introduced SLP to the problem of cabin equipment layout and combined it with GA to optimize the design.

There are multitasking states in the actual operation of ships, and there are different human flow and logistics requirements between cabins in different states. Hence, optimizing the layout of cabins based on the human flow and logistics in one state is unreasonable. The optimal plan must meet the needs of various states. Accordingly, it is important to rationally integrate the human flow and logistics in multitasking states into a parameter scheme. Wang et al. (2012) selected the battle state, damage control state, emergency escape state, and supply support state of the ship and linearly weighted the circulation demand in each state to solve the multi-objective model of the optimization of the ship channel layout.

Most optimization models of the ship design are based on the idea of deterministic optimization, but in actual engineering problems, there are generally uncertain factors. In the optimization problem of the cabin layout design, the artificial quantification of adjacent and circulating requirements between cabins into parameters encounters errors. The human flow and logistics between cabins are uncontrollable in actual operations, and the coupling shows typical uncertainties. In the multitasking state, there are a variety of human flows and logistics requirements, which makes the uncertainty more complicated.

To produce a cabin layout plan that meets the demand of the human flow and logistics in multitasking states, in the deterministic optimization method, the linear weighted summation method is used to forcibly combine the requirements in different states, which do not have realistic interpretability. After many iterations, the uncertainty will be further coupled and amplified. The uncertainty optimization method is adopted, and the influence of uncertainty factors is fully considered in each iteration, resulting in an optimization process with higher stability and compatibility.

Uncertainty optimization is a reliable method that considers the influence of uncertain factors on the optimization model on the basis of deterministic optimization problems. Based on the characteristics of uncertain parameters, uncertainty optimization can be divided into stochastic programming, fuzzy programming, and interval programming. Interval programming, that is, interval optimization, is used to express uncertain parameters with interval numbers, and it is necessary to obtain the endpoints of interval numbers to determine the midpoint and radius of the interval. In the ship design optimization problem, it is difficult to obtain the probability distribution of uncertain parameters and the fuzzy membership function, but it is relatively easy to obtain the endpoints of interval numbers. The initial information of uncertain parameters is not affected by the interval number, so applying the interval optimization method to ship design has certain advantages.

Based on the advantages of the interval optimization method, interval optimization has been widely used in the field of ship design in recent years. Li et al. (2018) applied the interval analysis method to the uncertainty and robust design optimization and used a bulk carrier as an example to optimize the existence of a single uncertain variable and the coexistence of multiple uncertain variables; Hou et al. (2016-2017) used interval numbers to describe the uncertainty of the approximate model of the wave resistance coefficient constructed by the backpropagation neural network and constructed and solved the optimization model of the minimum total resistance. He also applied the interval optimization method to the minimum Energy Efficiency Operation Index hull line design and verified its feasibility and superiority through calculations. Wen et al. (2016) developed an interval optimization method in the power system of a hybrid ship to determine the optimal size of the solar energy and energy storage system in the ship power system to reduce fuel costs. The above research reflects the applicability and superiority of interval optimization in ship design, and the proposed method can be applied to the layout design of ship cabins.

In this research, the interval optimization method is applied to the layout design of ship cabins, the living area of the ship deck is taken as the research object, and a simplified layout model is constructed. Based on the literature, a mathematical model is established with the cabin sequence as a design variable. Four task states are selected in the process of ship operations, with different adjacent and circulating strength coefficients in each state. First, deterministic optimization was performed, and the improved GA was used to optimize the calculation of the strength coefficient of the ship in one state and multiple states. Then, the interval was optimized using interval numbers to represent the adjacent and circulating strength coefficients, and an optimization system of two-layer nested was applied. The outer layer uses an improved GA to optimize the objective function, and the inner layer uses an SA algorithm to solve the interval of the objective function. Then, the results of the interval and deterministic optimization were compared and analyzed, and the rationality and effectiveness of the interval optimization method were discussed.

2 Layout Simplified Model

To solve the optimal layout of the ship cabin layout, the two-dimensional FLP method was applied, combined with the multi-line layout method, to simplify the cabin regions of the ship's living area (Kirtley, 2009; Han et al., 2015).

Selecting the cabin regions of the living area to establish a simplified model is based on the regions having a neat structure, and there is less equipment in the cabin. It is assumed that the cabin layout of the living area has no effect on the navigation performance, ship's weight distribution, hull's structure strength, and equipment performance. The layout of stairways, doors, windows, and other accessories is not considered.

A rectangle was drawn based on the longest and shortest sides of the cabin area structure. The horizontal and longitudinal channels were used to enclose five areas inside the rectangle. The five areas were simplified into rectangles, and their layout positions remained unchanged. The simplified model of the cabin layout is shown in Figure 1.

In Figure 1a, the solid line represents the cabin area structure of the living area, and the dashed enclosed area represents the area to be deployed. In Figure 1b, the solid line represents the simplified cabin area structure.

3 Mathematical Model

In this research, the cabin sequence was used as a design variable. The target's analysis was performed from the perspective of the circulating and adjacent relationships between the cabins. The sub-objective evaluation functions were constructed separately and then linearly weighted to form the overall objective evaluation function to appraise the performance.

3.1 Design Variable

The sequence of cabins is composed of the serial numbers of cabins in an array based on the sequence of the layout positions of cabins. The cabin sequence X is expressed as

$$X = \{x_1, x_2, x_3, \cdots, x_n\} \tag{1}$$

and

$$\begin{cases} x_k = \{x \mid x \in N^*, 1 \le x \le n\}, (k = 1,2, \cdots, n) \\ x_i \ne x_j, (i,j = 1,2, \cdots, n, i \ne j) \end{cases} \tag{2}$$

where n represents the total number of cabins to be deployed, and x_k represents the serial numbers of the cabins corresponding to the location.

Based on the cabin sequence X, the distance between cabins is calculated on the basis of the simplified model of the cabin layout.

First, the network diagram was established with nodes and connecting lines. The cabin node is the cabin centroid. The intersection of the core and the vertical line between the channel center line and cabin centroid is the channel node. The channel connecting line is composed of the vertical line between the channel center line and cabin centroid and the channel center line. The deck, after arranging the cabins, can be abstracted as a network diagram (Wu et al. 2019), as shown in Figure 2.

The stairway node is a connection node of the two decks. The shortest distance between cabin i and cabin j can be abstracted as the distance from point x_i to point x_j. There are two different paths a and b at the same time, and there will be up to eight different paths between different floors of cabins.

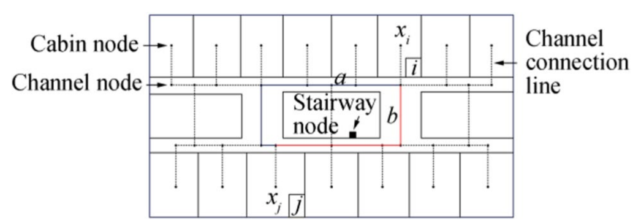
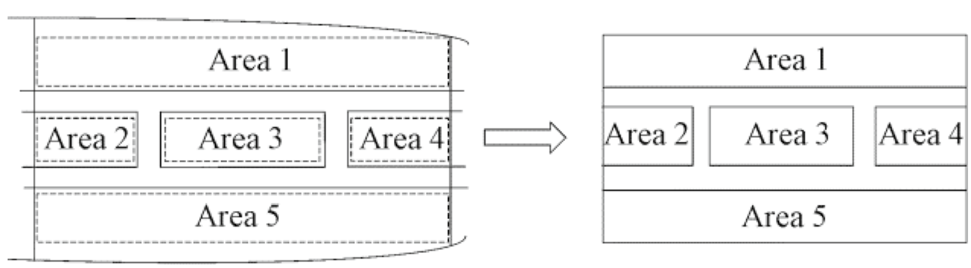


Figure 2 Simplified process of the cabin layout

Figure 1 Simplified process of the cabin layout



The distance between cabins varies with paths, and choosing a different path has a direct impact on the human flow and logistics between cabins. The distance between the cabins with adjacent requirements is far. The layout efficiency and effectiveness of the overall layout plan are even worse. Therefore, the shortest distance between cabins is an important indicator to evaluate the pros and cons of the layout plan, and it is important to determine the shortest path and distance.

Classic graph theory algorithms for solving the shortest distance include Dijkstra's algorithm and Floyd's algorithm. Among them, Dijkstra's algorithm is the most stable shortest-path algorithm and has the advantage of low complexity (Wu, 2019; Rahayuda et al., 2021). The process is shown in Figure 3.

The shortest distance calculated by Dijkstra's algorithm is stored in the matrix $\boldsymbol{D}$.

$$\boldsymbol{D} = \left[d_{ij}\right]_{n\times n}, (i,j = 1,2, \cdots, n, i \neq j) \tag{3}$$

where d_{ij} represents the shortest distance between cabins i and j.

3.2 Sub-objective Evaluation Function

In this research, starting from the adjacent and circulating relationships between cabins, we quantified the degree of association between cabins and established adjacent sub-objective and circulating sub-objective functions.

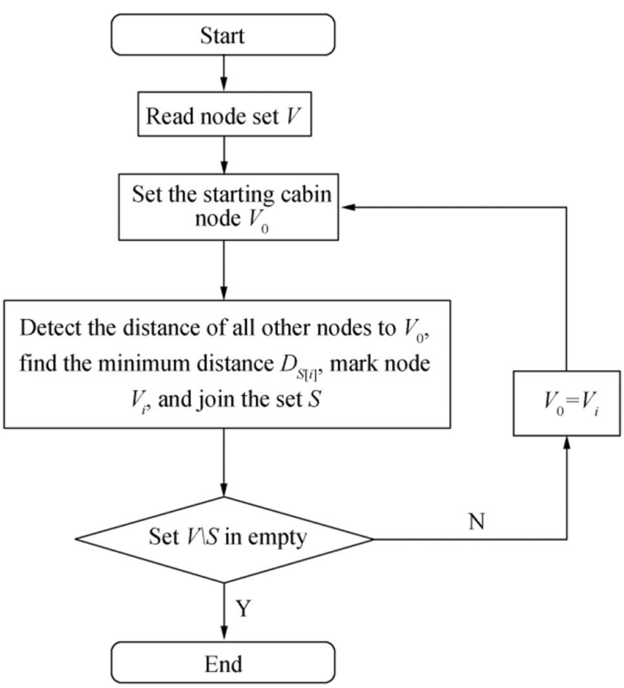


Figure 3 Dijkstra's algorithm flow chart

3.2.1 Target of the Adjacent Strength

The strength of the adjacency between cabins is the degree of adjacent requirements between two cabins to be deployed based on functional and usage requirements. It is quantified and expressed in parameterized form. The coefficient is represented by numbers 0–1. The larger the value, the higher the adjacent demand. The coefficients' value is stored in matrix $\boldsymbol{B}$:

$$B = \left[b_{ij}\right]_{n\times n}, (i,j = 1, 2, \cdots, n, i \neq j) \tag{4}$$

where b_{ij} represents the value of adjacent strength coefficients between cabins i and j.

The adjacent strength sub-objective function $F_1(X)$ is established as follows:

$$F_1(X) = \sum\nolimits_{i=1}^{n-1} \sum\nolimits_{j=i+1}^{n} B \times D(X) \tag{5}$$

where $D(X)$ represents the shortest distances' matrix between cabins.

3.2.2 Target of the Circulating Strength

The strength of the circulation between cabins mainly considers the strength of the circulating relationship between crews in the cabin during their daily activities. The coefficient is represented by numbers 0–1. The larger the value, the higher the circulating demand. The coefficients' value is stored in matrix $\boldsymbol{F}$:

$$F = \left[f_{ij}\right]_{n\times n}, (i,j = 1, 2, \cdots, n, i \neq j) \tag{6}$$

where f_{ij} represents the value of circulating strength coefficients between cabins i and j.

The circulating strength sub-objective function $F_2(X)$ is established as follows:

$$F_2(X) = \sum\nolimits_{i=1}^{n-1} \sum\nolimits_{j=i+1}^{n} F \times D(X) \tag{7}$$

3.3 Constraints of Location and Available Area

3.3.1 Location

In this research, the location constraint of the cabin is defined as the distance between two cabins and the requirement that the cabin is suitably arranged in a specific position. The degree to which a cabin needs to be far from another cabin is quantified. The coefficient obtained after quantization is represented by numbers 0–1. The coefficient is stored in matrix $\boldsymbol{A}$.

$$A = \left[a_{ij}\right]_{n\times n}, (i, j = 1, 2, \cdots, n, i \neq j) \tag{8}$$

where a_{ij} represents the value of strength coefficients between cabins i and j.

The requirements for the suitable arrangement of the cabin in a specific position should be determined based on the layout of the mother ship and combined with layout standards. For example, cabins 1 and 11 can be arranged in the middle of the upper deck, whereas cabins 7, 33, and 44 can be arranged in the lower deck.

$$\begin{cases} \left\{x_1, x_{11}\right\} \in \{1\} \\ \left\{x_7, x_{33}, x_{44}\right\} \in \{2\} \end{cases} \tag{9}$$

where 1 and 2 represent the upper and lower decks, respectively.

3.3.2 Available Areas

Based on the basic framework of the cabin area to be deployed, the usable area $\boldsymbol{S_i}(\boldsymbol{i} = 1, 2, \cdots, \boldsymbol{m})$ of each row and the minimum areas' reference of each cabin $\boldsymbol{\alpha}\left(\boldsymbol{x_j}\right)(\boldsymbol{j} = 1, 2 \cdots, \boldsymbol{n})$ are obtained. The cabin sequence $\boldsymbol{X}$ is sequentially arranged in the cabin area. The minimum area of the cabin arranged in each row is required to be no more than the usable area of the row:

$$\begin{cases} \alpha\left(x_1\right) + \alpha\left(x_2\right) + \alpha\left(x_3\right) \le S_1 \\ \alpha\left(x_4\right) + \alpha\left(x_5\right) + \alpha\left(x_6\right) + \alpha\left(x_7\right) \le S_2 \\ \cdots \\ \alpha\left(x_{n-2}\right) + \alpha\left(x_{n-1}\right) + \alpha\left(x_n\right) \le S_m \end{cases} \tag{10}$$

where m represents the maximum number of rows divided by the longitudinal channel and $\alpha\left(x_j\right)$ represents the minimum areas' reference of the cabin corresponding to the location.

For the cabin sequence X that meets the available areas' constraints, each row may have a remaining area, which is equally distributed to each cabin. The revised cabin area is used to determine layout parameters corresponding to the cabin sequence X.

$$\begin{cases} \beta\left(x_1\right) + \beta\left(x_2\right) + \beta\left(x_3\right) = S_1 \\ \beta\left(x_4\right) + \beta\left(x_5\right) + \beta\left(x_6\right) + \beta\left(x_7\right) = S_2 \\ \cdots \\ \beta\left(x_{n-2}\right) + \beta\left(x_{n-1}\right) + \beta\left(x_n\right) = S_m \end{cases} \tag{11}$$

where $\beta\left(x_j\right)$ represents the area of the cabin after correction.

3.4 Overall Objective Evaluation Function

The overall objective function $F(X)$ for the optimization of the cabin layout contains two sub-objective functions. In view of the uncertain importance of the sub-objective functions, this research adopts linear weighting processing, and the overall objective function is expressed as follows:

$$\min F(X) = \min \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \begin{pmatrix} w_1 \times b_{ij} \times d_{ij} \\ +w_2 \times f_{ij} \times d_{ij} \end{pmatrix} \tag{12}$$

and

$$\sum_{h=1}^{2} w_h = 1, X = \left\{x_1, x_2, x_3 \cdots, x_n\right\} \tag{13}$$

where w_1 is the weighting coefficient of the adjacent strength and w_2 is the weighting coefficient of the circulating strength. They are determined according to the importance of the sub-targets, and the sum of the two weighting coefficients is 1. The optimization goal of this research is to obtain the minimum value of the overall objective function $F(X)$ in the feasible region of the cabins sequence X, that is, to obtain the optimal cabin sequence X that satisfies constraints. The adjacent strength and circulating strength sub-objectives can reach a comprehensive optimum.

4 Deterministic Optimization

4.1 Deterministic Optimization in a Single-Task State

Before performing optimization, we must determine the initial parameter value and initial variable for the layout design (Tables 1, 2 and 3).

The intensity requirement is quantified as an intensity coefficient, which is represented by 0–1. The larger the value, the higher the requirement. The numbers in brackets indicate a group of cabins with strength requirements. For instance, 0.4 (1–7) means that the strength coefficient of cabins 1 and 7 is 0.4.

C1#, C2#, and C3# represent three different calculation cases.

The GA provides a general framework for solving complex optimization problems. It does not depend on the specific field of the problem, can be flexibly improved, and has strong robustness (Su et al., 2020).

This study has made some improvements to the basic GA in practical applications (Hu et al., 2014). For example, in the initial population generation method, the individual in the solution space of the optimization problem is directly encoded, and the decoding step is omitted, which is more convenient and feasible than the binary encoding method adopted by the basic GA. Based on the general framework, an improved GA suitable for solving the cabin layout model was constructed.

C1# selects state 1 for the calculation case and applies an improved GA to calculate. The optimal solution was searched through iteration, and the optimal result of deterministic optimization was obtained after 10 000 iterations,

Table 1 Initial values of the design variables and layout parameters

Design variables	Cabin sequence	X
Layout parameters	Minimum area of the cabin (m^2)	$\alpha(x_j) \in \{10,12,13,15,16,17,18,19,20,26,30\}$
	Total length of the deck area (m)	40
	Total width of the deck area (m)	20
	Height between decks (m)	2.3
	Number of horizontal channels	2
	Number of longitudinal channels	2
	Channel width (m)	1.5

Table 2 Initial values of strength in each state

Task states	State 1	State 2	State 3	State 4
Coefficient of the adjacent strength	0.4 (1–7)	0.4 (2–11)	0.6 (9–15)	0.7 (2–11)
	1 (33–46)	0.3 (17–27)	0.3 (35–39)	0.5 (35–39)
	0.5 (56–60)	0.5 (56–60)	0.4 (56–60)	0.7 (66–79)
	1 (66–79)	0.5 (66–79)	0.9 (66–79)	0.5 (77–78)
Coefficient of the circulating strength	0.6 (1–4)	0.8 (9–10)	1 (41–46)	1 (13–31)
	0.7 (9–10)	0.5 (27–67)	0.4 (44–55)	0.6 (44–55)
	0.5 (41–46)	0.5 (44–55)	0.9 (50–60)	0.4 (50–60)
	0.7 (50–60)	0.3 (50–60)	0.4 (70–80)	0.2 (72–73)

Table 3 Calculation cases

Case	Optimization method	Algorithm	States
C1#	Deterministic optimization	GA	State 1
C2#	Deterministic optimization	GA	States 1–4
C3#	Interval optimization	GA + SA	States 1–4

as shown in Figure 4. The optimal result is obtained in the 8536th calculation, represented by a red rectangle, with a value of 0.405.

A cabin layout result diagram was then generated after the calculation, as shown in Figure 5. The diagram shows the number of feasible and optimized solutions generated through continuous calculations and displays the fitness value of the objective function and layout of cabins on the two decks (Wang et al., 2016).

The yellow rectangular frame in the figure represents the cabin, the number in it represents the serial number of the cabin, the gray area represents the horizontal and longitudinal passages, and Sw1 and Sw2 indicate the entrance and exit of the stairway, respectively. The red rectangular frame is the originally given position of the horizontal passage, which needs to be moved due to the specific situation of the cabin layout. After movement, it is represented by the gray rectangular frame. The translation amount of the horizontal passage in the figure is caused by this. The area of each cabin in the figure is the revised cabin area $\beta(x_j)$ that satisfies the available area constraint.

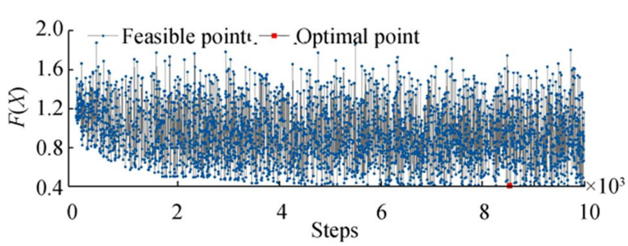


Figure 4 Optimization curve of the overall objective function for C1#

4.2 Deterministic Optimization in the Multitasking State

Deterministic optimization was performed in the multitasking state, and the linear weighted-sum method was selected to integrate the human flow and logistics requirements in the four task states into a plan. To ensure the effectiveness of the comparison with the interval optimization results, the weight coefficient of each state λ_k takes the weight coefficient k_i used in the interval optimization below: $\lambda_i = \{0.33, 0.16, 0.28, 0.23\}$.

In C2#, after linear weighting, the strengths of the adjacency and circulation coefficients were obtained, and the improved GA was used for the calculation. The optimization

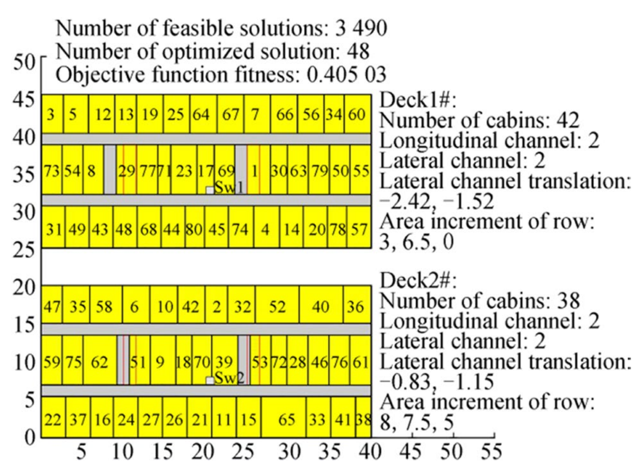


Figure 5 Diagram of the cabin layout for C1#

curve of the overall objective function was obtained after 10 000 iterations, as shown in Figure 6, where the 8941st calculation obtained the optimal result, represented by a red rectangle, with a value of 0.4219.

After the calculation, the layout result diagram was generated, as shown in Figure 7.

5 Interval Optimization

5.1 Determination of the Number of Intervals

Based on the superiority of the interval optimization method in the field of ship design, the method was selected to optimize the cabin layout in a multitasking state (Guo et al., 2008). The interval number is a kind of numerical value represented by the interval, which can be expressed as,

$$A^I = \left[A^L, A^R\right] \tag{14}$$

where A^L and A^R represent the upper and lower limits of the interval number, respectively, $A^L, A^R \in R$, and $A^L \le A^R$. When $A^L = A^R$, A^I is a real number.

The number of intervals is determined by the coefficient values of the adjacent and circulating strengths in

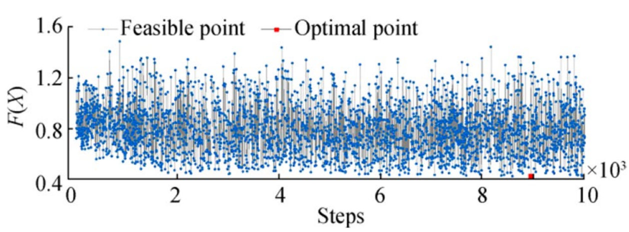


Figure 6 Optimization curve of the overall objective function for C2#

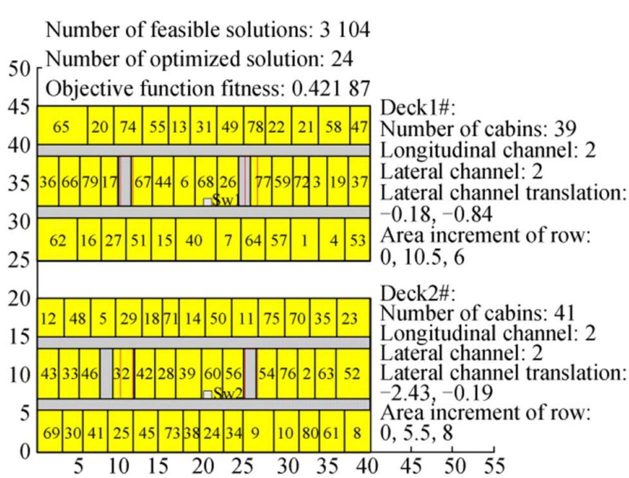


Figure 7 Diagram of the cabin layout for C2#

multitasking states combined with the weight of its state. The weight of each state is determined by integrating the proportion of the state in the entire operating life cycle and experts' opinions.

$$k_i = \frac{w_i \overline{w}_i}{\sum_{i=1}^{n} w_i \overline{w}_i} \tag{15}$$

and

$$\sum_{i=1}^{n} k_i = 1 \tag{16}$$

where w_i represents the proportion of the state in the entire operating life cycle, $\overline{w}_i$ represents the proportion of experts' opinions, k_i represents the weight of the target state, and n represents the number of target states.

The weights of the multitasking states were combined to determine the end point of the interval number (Fig. 8).

$$p_s = \left[a_i, a_j\right] \tag{17}$$

and

$$\begin{cases} o = \frac{a_1 + a_s}{2}, a_j > a_i \\ \begin{cases} m = num\left\{a_w < o | w \in [1, s]\right\} \\ n = num\left\{a_u > o | u \in [1, s]\right\} \\ m + n \le s \end{cases} \\ \begin{cases} a_i = o - \left(a_s - a_1\right) \times \frac{\sum_{i=1}^{m} k_i}{\sum_{i=1}^{s} k_i} \\ a_j = o + \left(a_s - a_1\right) \times \frac{\sum_{i=s-n+1}^{s} k_i}{\sum_{i=1}^{s} k_i} \end{cases} \end{cases} \tag{18}$$

where p_s represents the number of intervals of the adjacent and circulating strength coefficients in various states. a_i and a_j represent the upper and lower limits of the interval, respectively, and $a_i < a_j$. s indicates that the coefficient exists in several states. o represents the midpoint of the interval. num represents the number of elements in the set. m represents the number of coefficient values less than the midpoint, and n represents the number of coefficient values greater than the midpoint. k_i represents the weight of the target state. $\left\{a_1, a_2, \cdots, a_s\right\}$ represent the coefficient values in different states, and they are arranged in $1 - s$ from small to large).

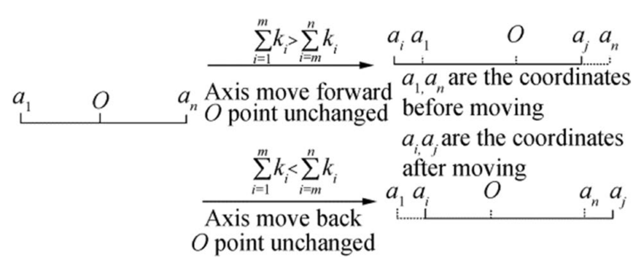


Figure 8 Determining the end points of the interval number

5.2 Theory of Interval Optimization

This research uses interval numbers to describe uncertain variables (Li et al., 2010). The main idea is to use the midpoint and radius of the objective function to evaluate the pros and cons of different design variables, thereby obtaining a deterministic objective function.

$$\text{opt}\ \min f_p = \min \left\{ \begin{array}{c} (1-\beta)\mu\left(f\left(X, p_m\right)\right) \\ +\beta\omega\left(f\left(X, p_m\right)\right) \end{array} \right\} \tag{19}$$

and

$$\left\{ \begin{array}{l} \mu\left(f\left(X,\ p_m\right)\right) = \frac{\left(\min f\left(X,\ p_m\right) + \max f\left(X,\ p_m\right)\right)}{2} \\ \omega\left(f\left(X,\ p_m\right)\right) = \frac{\left(\min f\left(X,\ p_m\right) - \max f\left(X,\ p_m\right)\right)}{2} \end{array} \right. \tag{20}$$

where β is the weight coefficient, which satisfies $0 \le \beta \le 1$ and generally takes 0.5, $\mu\left(f\left(X, p_m\right)\right)$ is the midpoint of the objective function, and $\omega\left(f\left(X, p_m\right)\right)$ is the radius of the objective function.

The above optimization model is an optimization problem with interval numbers, and its corresponding objective function is not a specific real number in the optimization iteration but an interval number. Therefore, the interval analysis method needs to be integrated into the entire optimization process to realize the calculation of interval numbers (Li et al., 2015). Without considering the optimization strategy, the optimization problem is transformed into a two-layer nested optimization problem (Zhang, 2015a). A two-layer nested optimization system is used for uncertainty optimization, and the structure is shown in Figure 9.

The outer-layer optimization is used to search for design variables, and the inner layer optimization is used to calculate the interval of the uncertain objective function. That is, the individual design variables are generated through outer-layer calculations. Each individual uses the inner algorithm to obtain the uncertain objective function and constraint interval. Then, it is transformed into the objective function of deterministic optimization.

The task of outer-layer optimization is to generate individual design variables with wide coverage on a global scale. The algorithm used is required to have a strong traversal search ability. The improved GA is based on the general framework of the GA and combined with some improvements in the issue of the cabin layout. It has a fast random search capability and strong robustness and can be better adapted to the issue of cabin layout optimization after improvement.

Inner-layer optimization is the core of the uncertain optimization system. It has high requirements on the local search capability and computational efficiency of the algorithm. The SA algorithm has been proven to be strict and effective by long-term research and application. Compared with other intelligent algorithms, it has a wider application range, simpler algorithm, and easier realization. Its search method can effectively avoid falling into the local optimal solution and obtain a global optimal solution with high reliability, which is highly suitable for the calculation of cabin layout optimization.

Before optimization, we must determine the end points of the interval number and apply Eq. (15) to calculate the weights of the four task states: $k_i = \{0.33, 0.16, 0.28, 0.23\}$.

The number of intervals is determined by the values of the intensity coefficient under each state combined with the weight occupied (Table 4).

C3# applies the interval optimization method. The outer optimizer selects an improved GA and sets 10 000 iterations. The inner optimizer selects the SA algorithm and sets the initial temperature to 10 000 °C, the end temperature to 0.01 °C, and the temperature attenuation coefficient to 0.9. The optimal result of the interval optimization was obtained after the iterative optimization, as shown in Figure 10. Among

Figure 9 Two-layer nested structure

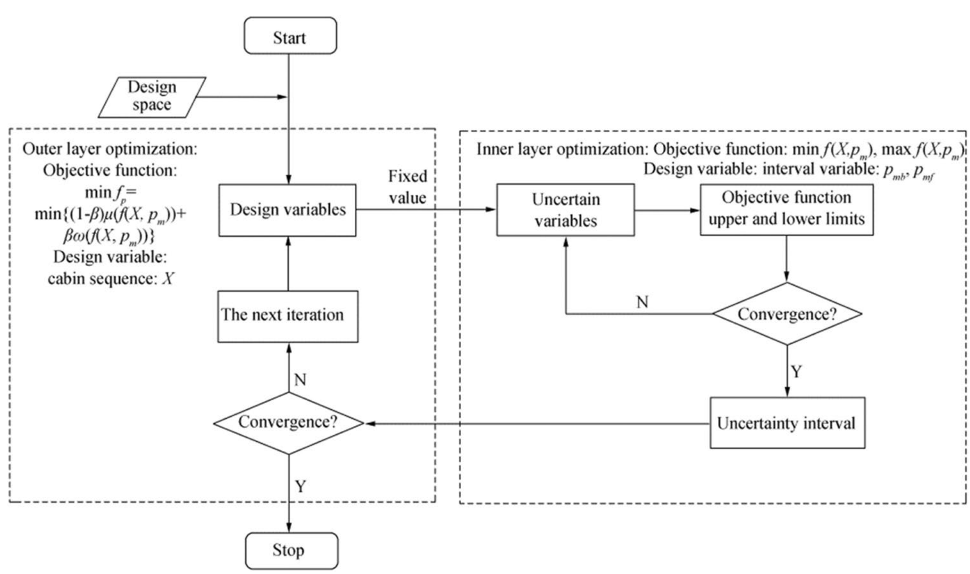


Table 4 Interval values of the adjacent and circulating strengths

Number of intervals	Values	Corresponding cabin group
Number of adjacent strength intervals p_{mb}	[0.427, 0.727]	2–11
	[0.29, 0.49]	35–39
	[0.414, 0.514]	56–60
	[0.555, 1]	66–79
Number of circulating strength intervals p_{mf}	[0.683, 0.783]	9–10
	[0.48, 0.98]	41–46
	[0.39, 0.59]	44–55
	[0.366, 0.966]	50–60

them, the optimal result is obtained in the 8663rd calculation, which is represented by a red rectangle alone with a value of 0.4920.

When the optimal solution was obtained, the curve of the minimum value $\min f(X, p_m)$ and maximum value $\max f(X, p_m)$ of the objective function in the inner optimizer is as shown in Figure 11. The generated layout diagram of the interval optimization results is shown in Figure 12.

The two curves represent the change curve of $\min f(X, p_m)$ and $\max f(X, p_m)$. As the number of SA iterations increases, the values tend to be stable. The minimum and maximum values of the objective function in the inner optimizer are obtained.

5.3 Results and Analysis

Based on the calculated results, we compared the advantages and disadvantages of interval and deterministic optimizations.

5.3.1 Comparing the Shortest Paths

The cabin groups (27–67) and (77–78) were selected to compare the shortest path and distance. The red dotted line represents the shortest path in cabin groups (77–78), and the blue dotted line represents the shortest path in cabin groups (27–67).

The distance between the two paths in Figure 13b is significantly smaller than that in Figure 13a, and the two sets of cabins are more closely arranged. Interval optimization can better meet the needs of proximity between cabins. The two groups of cabins have adjacent and circulating requirements in states 2 and 4, respectively. Compared with deterministic optimization, which only considers state 1, interval optimization fully considers the influence of various states, which can better meet the layout requirements of cabins.

The cabin groups (9–15) and (72–73) were selected for comparison. The red dotted line represents the shortest path in cabin groups (9–15), the blue dotted line represents the shortest path in cabin groups (72–73).

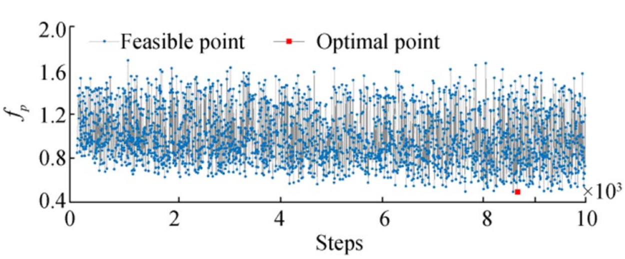


Figure 10 Optimization curve of the overall objective function for C3#

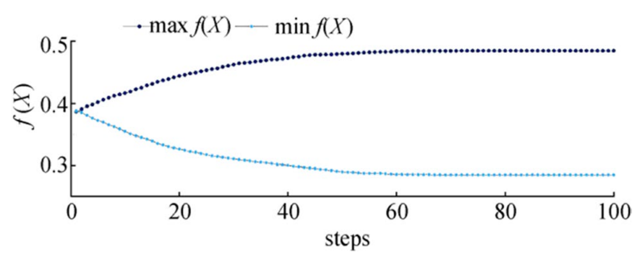


Figure 11 Optimization curve of the maximum and minimum values

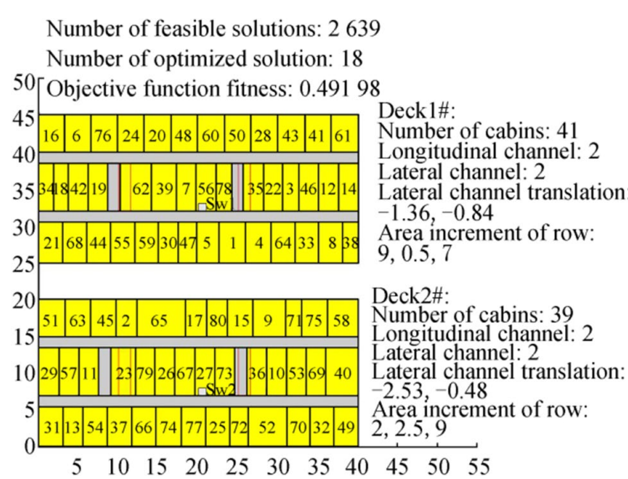
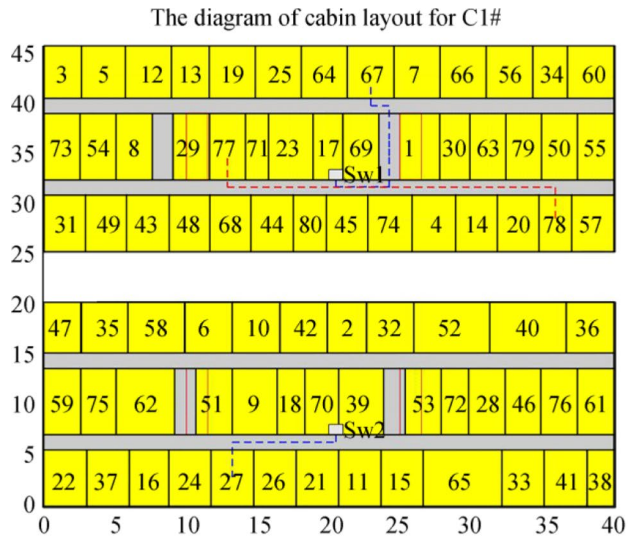
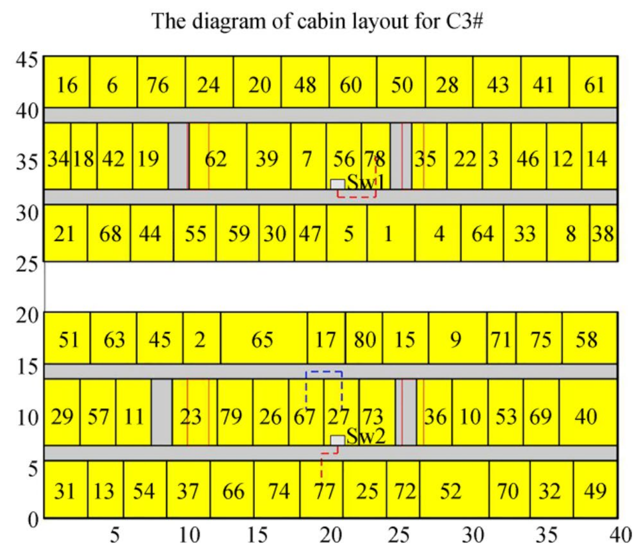


Figure 12 Diagram of the cabin layout for C3#



(a) Shortest paths in C1#



(b) Shortest paths in C3#

Figure 13 Comparison of distances between C1# and C3#

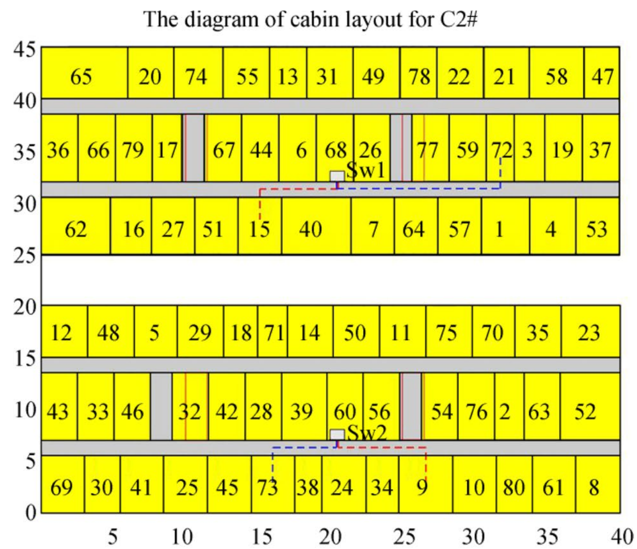
Based on the comparison of (a) and (b) in Figure 14, the distance between the two sets of cabins under the two methods is relatively small, which can better meet the needs of proximity between the cabins. Under the cabin layout obtained by the interval optimization, the distance between the two groups of cabins is smaller, and the obtained cabin layout is more reasonable. Compared with deterministic optimization considering multiple states, interval optimization has higher applicability and effectiveness for cabin layout problems in multitasking states.

As a whole, interval optimization can consider the layout requirements of multitasking states and can efficiently obtain a cabin layout plan that meets the demands of the immediate vicinity as much as possible. The interval optimization method is used to solve the problems of cabin layout in various states, which has high applicability and stability.

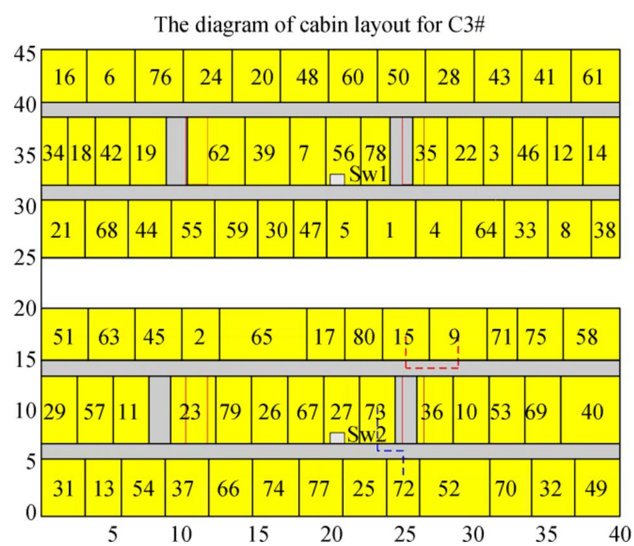
5.3.2 Comparing the Optimization Results

Based on the data in Table 5, the fitness curves are drawn in Figure 15.

As shown in Table 5 and Figure 15, C1# and C2# curves tend to be faster in a stable manner, whereas C3 # curves tend to be slower. Compared with interval optimization, deterministic optimization has better robustness. The fitness values of deterministic optimization are lower than those of interval optimization. By contrast, deterministic optimization can better meet the requirements of design objectives.



(a) Shortest paths in C1#



(b) Shortest paths in C3#

Figure 14 Comparison of distances between C2# and C3#

To better compare the advantages and disadvantages of the three methods, the distance d between cabins with adjacent requirements is summed according to the state, as shown in Figure 16.

As shown in Figure 16, the sum of distances of C1# in State 1 is small, whereas that in other states is relatively large. Here, only the requirements in State 1 are considered, so the compatibility of requirements in States 2, 3, and 4 is extremely poor.

In C2#, the sum of the cabins' distances under each state of the adjacent strength greatly fluctuates, and the distance is higher than that of C1# in State 1. By contrast, the distances under States 2, 3, and 4 are all smaller than those in C1#. The sum of the cabins' distances in each state under the circulating strength is relatively even, and the distance in each state is less than C1#. The smaller the distance between the cabins on demand, the better the adjacent and circulating requirements between the cabins can be met, and the higher the degree of completion of the layout of cabins. Therefore, the linear weighted-sum method is used to integrate the requirements of multiple states, which is highly effective and can better consider the multitasking states of the ship.

In C3#, the sum of the cabins' distances under each state of adjacent and circulating strengths is relatively average, and its distance value is less than C1# in each state. Compared with C2#, although the distance is not much different in a small part of the state, the distance is smaller in most of the states. The smaller the distance, the more the adjacent and circulating needs between the cabins can be met, and the higher the completion of the cabin layout.

Although deterministic optimization has higher robustness, the interval optimization method is used to solve the problem of cabin layouts in various states. Moreover, it has extremely high applicability and effectiveness and has a high degree of compatibility for multitasking states in the ship operation process.

Table 5 Comparison of the optimization results of three cases

Calculation cases	Fitness values	Number of iterations
C1#	0.405	8536
C2#	0.4219	8941
C3#	0.492	8663

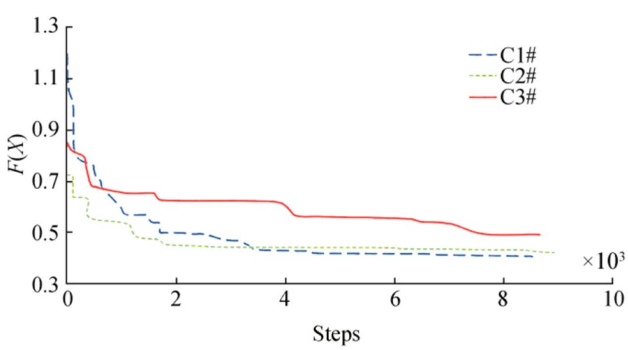


Figure 15 Curve of the optimal adaptive value of the three methods

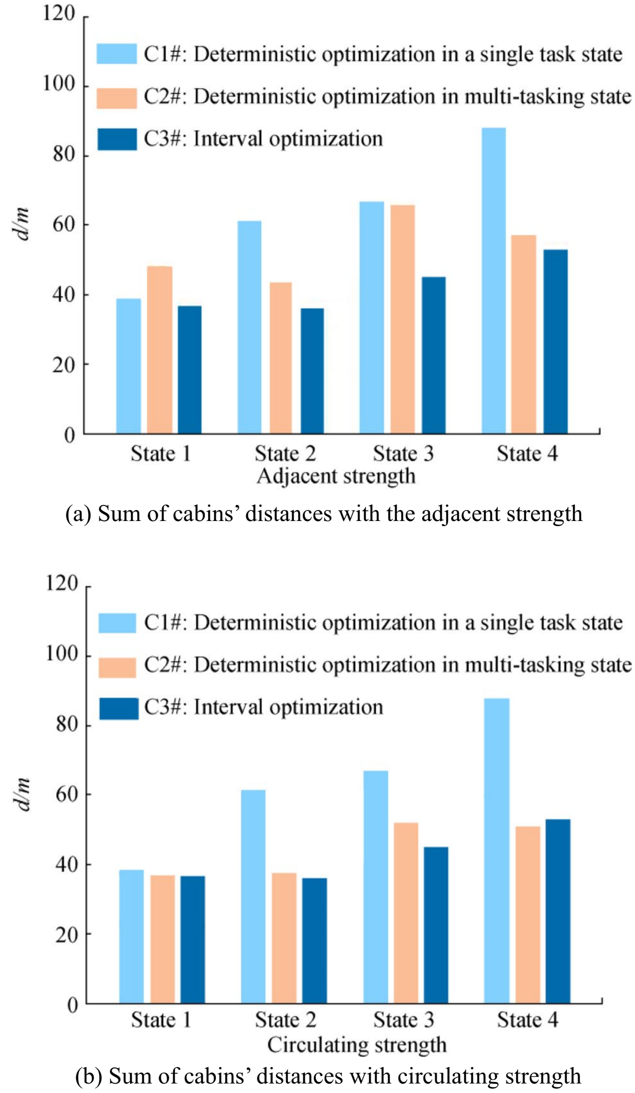


Figure 16 Sum of cabins' distances with adjacent and circulating strengths

6 Conclusions

Considering the different intensities and uncertainties of the human flow and logistics under different states, the deterministic and interval optimization methods are adopted in this study. After a series of calculations, analyses, and comparisons, the following conclusions are obtained:

1) Based on multitasking states, compared to deterministic optimization that only considers the demands of the immediate vicinity in a single state, interval optimization can better consider the demands of multiple states. Compared with the linear weighting method to integrate the demands under multitasking states, the representation of interval numbers can effectively obtain a better cabin layout plan. Applying the interval optimization method to the cabin layout problem can effectively solve the layout optimization problem and has high applicability, stability, and compatibility.
2) In deterministic optimization, an improved GA is applied to obtain a reasonable plan of cabin layout after calculations. The algorithm has good applicability in the field of cabin layout design. In interval optimization, a two-layer nested system is used: the outer-layer and inner-layer optimizations have different optimization goals, and the improved GA and SA algorithms are selected, respectively. After the calculation and analysis, reasonable and reliable optimization results are obtained. Hence, applying GA and SA algorithms to interval optimization has high applicability, and applying different optimization algorithms in the two-layer nested system can improve the effectiveness and reliability of the optimization process.
3) In this research, interval numbers are used to represent uncertain factors. Fuzzy and random numbers can be used to quantify uncertain factors, and uncertainties can be analyzed to further explore and solve their influence.

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