# Hybrid GA-PSO Model for Multi-objective Dynamic Optimization of Cruise Cabin Layouts under Marine Operational Constraints

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*Cruise cabin space design stands as a pivotal determinant of passenger experience and operational efficiency, yet it grapples with three core challenges: irregular spatial configurations shaped by hull curvature, dynamic demands (e.g., fluctuating passenger load, real-time activity needs), and inherent multi-objective conflicts (e.g., maximizing space utilization vs. ensuring comfort). Traditional optimization methods—such as standalone heuristic algorithms or static layout planning—are constrained by limited global search capabilities, sluggish convergence in complex scenarios, and inability to adapt to maritime dynamic constraints. To address these gaps, this study innovatively proposes a hybrid GA-PSO bimodal algorithm and constructs a dynamic cruise cabin space optimization model. Marine-specific dynamic constraints are explicitly modeled, including ship motion parameters (roll/pitch angles under sea conditions 3–8) and maritime evacuation regulations (minimum channel width ≥1.2m). Four mutually restrictive objective functions are also formalized: space utilization (ratio of effective area to total area), comfort (integrated score of ergonomic spacing/noise isolation), structural feasibility (compatibility with hull load-bearing limits), and life-cycle cost (construction + maintenance expenses).Experiments utilize 12 typical cabin layouts (200–300 m²), 500+ passenger behavior datasets (18 months of real-ship data), and 30 independent runs, comparing with standard GA and PSO. Results verify superiority: GA-PSO convergence speed reaches 0.80 ± 0.05 iterations/s (mean ± std), which is 38.7% faster than GA (0.58 ± 0.08 iter/s) and 22.1% faster than PSO (0.66 ± 0.07 iter/s). The improvement is statistically significant (p < 0.01, t-test).; optimal solution comprehensive value hits 0.92 (15.2% higher than GA, 9.8% than PSO), with statistical significance (p<0.05). It maintains 0% safety violations in dynamic scenarios, providing reliable intelligent decision support for cruise cabin design.*

*Povzetek: Študija predstavi hibridni algoritem za optimizacijo prostora v kabinah križark, ki hitreje najde boljše postavitve in ostaja zanesljiv tudi pri spreminjajočih se pogojih.*

## 1 Introduction

In today's booming global tourism market, cruise tourism —a unique and popular tourism mode —is attracting an increasing number of tourists with its comprehensive sea vacation experience. A cruise ship is not only a means of transportation but also a maritime mobile city that integrates accommodation, catering, entertainment, leisure, and other functions. Among them, cabin space, as the core component of cruise ships, is directly related to tourists' living comfort and overall tourism experience. With the intensification of market competition and the increasingly diversified needs of tourists, how to optimize the cabin space of cruise ships to improve space utilization efficiency, meet the individual needs of different tourist groups, and maximize benefits in the dynamically changing operating environment has become a key problem to be solved urgently in the cruise industry [1].

In the field of cruise cabin space optimization, traditional optimization methods are primarily based on static and single-objective analysis, which makes it difficult to adapt to the complex and dynamic actual situations in cruise operations. For example, factors such as seasonal fluctuations in tourist demand, differences in the passenger source structure of different voyages, and dynamic adjustments to onboard activities will all impact the efficiency and functional layout of cabin space. Therefore, there is a need for a model capable of dynamic and multi-objective optimization of cabin space to address these challenges better [2].

In recent years, intelligent optimization algorithms have been widely used in complex system optimization problems. As two classic intelligent optimization algorithms, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) have unique advantages. By simulating the biological evolution process, GA can effectively search for the global optimal solution, possessing strong global search ability and the ability to avoid falling into local optima. In contrast, PSO exhibits rapid convergence and ease of implementation by simulating the social behavior of bird groups. However, a single algorithm often has limitations when dealing with complex optimization problems; for example, GA may be slow in terms of convergence speed, while PSO may easily fall into a local optimum in the later stages. Therefore, the fusion of GA and PSO to form a dual-modal optimization algorithm can leverage the advantages of both algorithms, overcome their respective shortcomings, and provide more effective tools for solving complex optimization problems [3].

This study aims to construct a dynamic optimization model of cruise cabin space using a bimodal GA-PSO algorithm. The model will comprehensively consider a variety of dynamic factors related to cruise cabin space, including, but not limited to, matching cabin types with tourist needs, the flexibility of cabin layouts, and the balance of operating costs and benefits. By introducing the GA-PSO dual-modal algorithm, the model can quickly and accurately optimize the allocation and layout of cabin space in a dynamically changing environment, thereby achieving multi-objective optimization. This optimization enables improvements in the utilization rate of cabin space, tourist satisfaction, and reduced operating costs.

In the research process, it is first necessary to comprehensively analyze the characteristics and optimization requirements of cruise cabin space. This includes an in-depth study of the physical properties of cabin spaces, functional zoning, visitor behavior patterns, and operational constraints. By addressing these factors, the objective function and constraints of the optimization problem can be clarified, laying a foundation for subsequent model construction.

Secondly, the GA and PSO algorithms will be studied and analyzed in detail, with a focus on their principles, characteristics, and applications in optimization problems. On this basis, an effective GA-PSO bimodal algorithm framework is designed, and the organic combination of global search ability and local search ability is realized by reasonably integrating the advantages of the two algorithms. This will involve researching the coding mode, population initialization, genetic operation, and particle update strategy of the algorithm, as well as optimizing algorithm parameters.

In the model construction stage, based on the above research results, a mathematical model will be developed that dynamically optimizes the cabin space of cruise ships. The model will utilize the GA-PSO bimodal algorithm as an optimization solution tool and verify the effectiveness and practicality of the model by simulating various dynamic scenarios during cruise operations. During the model verification process, actual cruise operation data, including cabin reservation information, tourist feedback data, and operating cost data, will be collected. The advantages of the GA-PSO bimodal algorithm in dynamic optimization of cruise cabin space will be demonstrated through a comparative analysis with traditional optimization methods [4, 5].

Based on the above analysis, the GA-PSO bimodal algorithm proposed in this study is theoretically innovative. The aim is to explore a dynamic optimization model of cruise cabin space integrated with the GA-PSO dual-modal algorithm.

A new calculation method to build an efficient and accurate calculation framework to promote the development of the cruise field and provide strong technical support for applications in related fields. Through the innovative application of the bimodal algorithm, we aim to tap into the development potential of cruise enterprises more deeply, explore new avenues for promoting the sustainable development of the cruise industry, and provide new perspectives and ideas for research on the bimodal method.

While significant advances have been made in optimization algorithms, their application to cruise-specific challenges requires integration with principles from naval architecture, ergonomic design for marine environments, and cruise cabin layout regulations. This study bridges this gap by embedding these domain-specific constraints directly into the hybrid GA-PSO optimization framework.

The main work of this paper is as follows:

(1) Propose a modular space partition and multi-objective optimization framework;

(2) Design a GA-PSO bimodal fusion optimization algorithm;

(3) Establish a dynamic optimization verification and evaluation system.

# 2 Theoretical knowledge related to GA-PSO bimodal fusion optimization algorithm

## 2.1 GA

GA: Genetic Algorithm (GA), proposed by John Holland in 1975, is an evolutionary algorithm that simulates natural selection and genetic mechanisms via three core evolutionary operators—selection, crossover, and mutation—to achieve global search in complex optimization problems. It excels at exploring diverse solutions by maintaining population diversity, yet often suffers from slow convergence in later iterations.

Key components include chromosome coding (translating real-world variables into computable strings like binary or real-number formats), the fitness function (quantifying individual solution quality to guide selection), and evolutionary operators. Elite retention is integrated to directly preserve top-performing individuals across generations, mitigating loss of optimal solutions during iteration.

First, chromosome coding. Individuals in the solution space are represented by chromosomes. Common coding methods include: binary coding and vector $\vec{x} = (x_1, x_2, ..., x_n)$ mapping to binary string $\vec{s} = \{0,1\}^L$, where L is the length of the string.

Example: Encoding of real number $x \in [a,b]$,The calculation process is shown in formula (1):

$$s = bin\left( round\left( \frac{x-a}{(b-a)} \cdot (2^L - 1) \right) \right) (1)$$

Real number coding: chromosomes are directly represented by vector $\pm\vec{x} \in R^n$, which is suitable for continuous optimization problems. The second is the fitness function, which evaluates the quality of chromosomes, The calculation process is shown in formula (2):

$$Fitness(\vec{x}) = f(\vec{x}) \quad OR \quad Fitness(\vec{x}) = \frac{1}{1+f(\vec{x})} (2)$$

Here, $f(\vec{x})$ is the objective function. The fitness value drives the probability distribution of the selection operation. Next is the selection operator, which selects high-quality individuals from the population to enter the mating pool. The commonly used strategy is roulette wheel selection: the selection probability of individual $i$ is shown in formula (3):

$$P_i = \frac{Fitness(\vec{x}_i)}{\sum_{j=1}^{M} Fitness(\vec{x}_j)} (3)$$

In which $M$ is the population size, and the same tournament selection is to randomly select $k$ individuals and retain the ones with the highest fitness.

Championship selection: randomly select $k$ individuals ( $k$ is the size of the championship) and retain the ones with the highest fitness. The formal process is shown in formula (4):

$$s = argmax_{i \in T} f(x_i) (4)$$

Then comes the crossover operator, which simulates gene recombination and generates new individuals. Among them, single-point crossover is: the parent chromosome $\vec{s}_A = s_{A1}s_{A2}...s_{AL}, \vec{s}_B = s_{B1}s_{B2}...s_{BL}$ randomly selects the crossover point $c \in [1, L-1]$, The calculation process is shown in formula (5):

$$\begin{matrix} s_{A1}...s_{Ac} | \; s_{B(c+1)}...s_{BL} \\ s_{B1}...s_{Bc} | \; s_{A(c+1)}...s_{AL} \end{matrix} (5)$$

Arithmetic crossover (real number coding), The calculation process is shown in formula (6):

$$\vec{x}_{\text{new}} = \lambda\vec{x}_A + (1-\lambda)\vec{x}_B, \quad \lambda \in [0,1] (6)$$

The crossover probability $P_c$ (usually 0.6~0.9) controls the operation frequency.

Two-point crossover: extend the single-point crossover and randomly select two crossover points to enhance diversity. The calculation process is shown in formula (7):

$$C_1 = P_1[1:k_1] \oplus P_2[k_1+1:k_2] \oplus P_1[k_2+1:L], \quad C_2 = P_2[1:k_1] \oplus P_1[k_1+1:k_2] \oplus P_2 \; (7)$$

$k_1$ and $k_2$ are the intersection points $(1 \le k_1 < k_2 \le L)$.

Uniform crossover: each gene is inherited independently from the parent generation, which is suitable for binary or real number coding. The calculation process is shown in formula (8):

$$C_i = \begin{cases} P_{1i} & if r_i < 0.5 \\ P_{2i} & otherwise \end{cases} (8)$$

Then is the mutation operator, which introduces random perturbation to avoid premature convergence; bit flip mutation (binary coding): gene bit $s_k$ is flipped with probability $P_m$ (usually 0.001~0.01), The calculation process is shown in formula (9):

$$s_k^{'} = 1 - s_k \; (9)$$

Gaussian variation (real number coding), The calculation process is shown in formula (10):

$$x_k^{'} = x_k + \mathrm{N}\;(0,\sigma) \; (10)$$

$\sigma$ is the variation step length.

Exchange mutation: It is often used for permutation coding (such as traveling salesman problem), and randomly exchanges the positions of two genes. The calculation process is shown in formula (11):

$$x^{'} = x, \quad swap(x_i, x_j) \quad for\ randomly\ chosen\ i \neq j \; (11)$$

Where $\mathrm{swap}(x_i, x_j)$ represents the gene value of the swapped position $i$ and $j$.

Finally, population updating employs an elite retention strategy to prevent the loss of optimal solutions: the best individuals from the current generation are directly copied into the next. The remaining individuals are replaced by a new population generated through selection, crossover, and mutation. Genetic algorithms achieve efficient global search through bionic mechanisms, providing a general framework for solving complex optimization problems. The key to enhancing performance lies in the coordinated optimization of parameter design and operator operations. At the same time, the pattern theorem mathematically ensures the algorithm's ability to explore the solution space progressively.

## 2.2 PSO

Particle Swarm Optimization (PSO), proposed by Kennedy and Eberhart in 1995, is a swarm intelligence algorithm that mimics natural group behaviors like bird flocking or fish schooling. Each particle represents a candidate solution, updating its velocity and position by referencing two key benchmarks: its own historical best position (pBest) and the global best position (gBest) of the entire swarm [6].

This mechanism enables rapid convergence, yet risks trapping in local optima in complex search spaces. Its core strengths lie in a simple structure and minimal key parameters—including inertia weight (balancing exploration/exploitation) and learning factors (guiding individual/group learning)—making it easy to implement across engineering and optimization scenarios [7].

The core principle of its algorithm is:

Let the search space be D-dimensional and the population contain M particles. The state of the $i$ -th particle at time $t$ is defined by two vectors: position vector: $\vec{X}_i(t) = (x_{i1}(t), x_{i2}(t), \ldots, x_{iD}(t))$ represents the current coordinate of the particle in the solution space, corresponding to a candidate solution.

Velocity vector: $\vec{V}_i(t) = (v_{i1}(t), v_{i2}(t), \ldots, v_{iD}(t))$ controls the direction and distance of the next move of the particle [8].

Particles search by iteratively updating their speed and position, and their update rules combine individual experience with collective wisdom: the optimal position of an individual is $\vec{P}_i(t)$ .

Record the optimal position experienced by particle I from initialization to time t. Global optimal position: $\vec{G}(t)$ record the optimal position found by the whole population so far (all particles share this information in standard PSO) [9], Its specific architecture is shown in Figure 1:

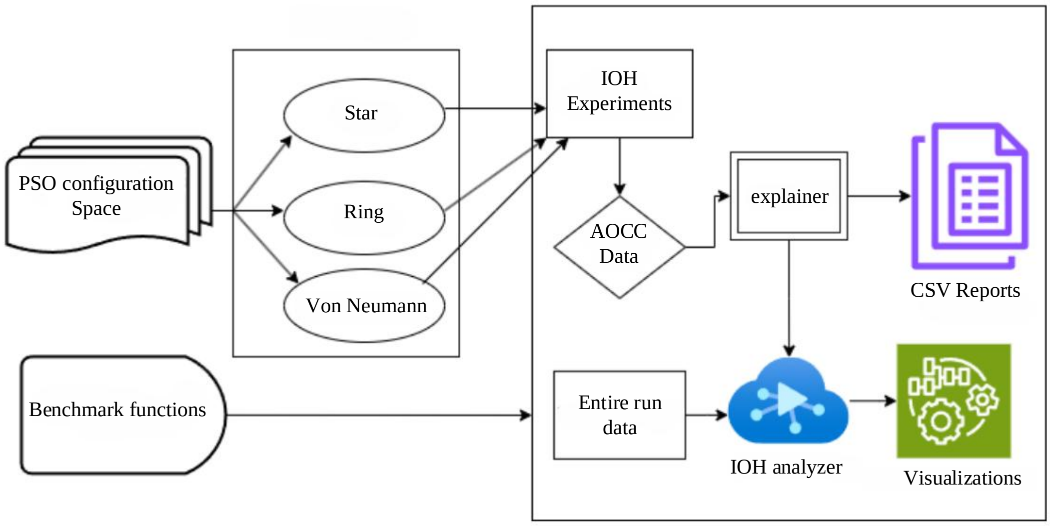


Figure 1: PSO network architecture diagram

## 2.3 Dynamic optimization framework for cruise cabin space

Dynamic optimization of cruise cabin space is a systematic design method aiming at the complex environmental constraints in ship navigation. Its core goal is to collaboratively optimize the four key goals of space utilization, passenger comfort, safety compliance, and functional adaptability within the limited cabin volume and to form an intelligent layout scheme that can respond to dynamic scenarios [10]. The theoretical basis covers the following key directions:

Dynamic constraint modeling theory: Cruise cabin design should strictly follow the dual constraints of ship kinematics and safety regulations. During the navigation, the cabin is continuously affected by the compound motion of roll and pitch caused by waves. This kind of motion characteristic requires that the layout suppress the risk of object displacement, and the centroid projection of furniture and equipment must always be located in the stable support area to avoid the slipping or capsizing of objects caused by the capsizing moment of the ship [11].

Multi-objective optimization problems refer to optimization issues where trade-offs are made between multiple objective functions. Unlike single-objective optimization, multi-objective optimization typically does not have a unique optimal solution but rather a set of non-dominated solutions, known as Pareto optimal solutions. The definition of a Pareto optimal solution is as follows: for any solution $x$ in the solution set, there is no other solution $y$ such that all objective function values at $y$ are better than those at $x$. multi-objective optimization problems can be expressed as formulas (12) and (13):

$$\min f(x) = [f_1(x), f_2(x), \ldots, f_k(x)] \quad (12)$$

$$s.t\ x \in \Omega (13)$$

Among them, $f(x)$ is the objective function vector, $k$ is the number of objective functions, and $\Omega$ is the feasible solution space.

At the same time, the International Convention for the Safety of Life at Sea establishes mandatory requirements for emergency evacuation, specifying that the width of the cabin passage must be dynamically adjusted according to real-time crowd density to ensure that the 90-second evacuation limit is met at all times. The essence of such constraints is that a time-varying spatial topology problem arises: the layout scheme needs to be reconstructed in real-time in response to changes in ship motion state, passenger distribution, and usage scenarios to form a dynamic safety boundary [12].

Multi-objective collaborative optimization framework: Cabin space optimization requires balancing four types of conflicting goals. First, maximize space utilization: under the constraints of fixed structures such as columns and pipes, the effective use volume is increased through modular furniture combinations and deformable partitions. The key to optimization lies in identifying "plastic areas" in irregular spaces, such as utilizing bulkhead curved surfaces to embed storage units or superimposing functional areas through folding mechanisms. Secondly, a dynamic guarantee of comfort is essential, as comfort encompasses both physiological and psychological dimensions [13]. At the physiological level, it is necessary to inhibit the effect of motion sickness and reduce the vestibular stimulation of the inner ear by adjusting the angle between the bed orientation and the main axis of ship rolling. At the psychological level, it is necessary to balance the sense of spatial transparency and privacy, such as using electronically controlled atomized glass to achieve light adjustment in both living and sleeping modes. Strengthening safety compliance again: In addition to evacuation passages, impact resistance design under sudden sea conditions should also be considered [14]. For example, the anchorage points of furniture need to disperse the stress load to avoid structural failure caused by local overload. The layout of electrical equipment must be far away from the low area of the cabin where water may seep. Finally, the functional adaptability is upgraded: the modern cruise cabin needs to be switched between daytime living, night sleeping, emergency avoidance, and other modes. This requires the establishment of "space function" mapping rules, such as storing the bed as a sofa during the day to release the active area and automatically retracting the coffee table to keep the passage open when unfolding the bed at night [15].

Environmental Response Mechanism: The core of dynamic optimization of cabin space lies in building a closed-loop system for environmental perception, decision-making, and execution, which is divided into three layers. The first is the perception layer: a real-time collection of ship six-degree-of-freedom motion data (roll/pitch/heave) through an inertial measurement unit, combined with cabin sensors to monitor people flow density, furniture status, and environmental parameters (temperature, humidity, illumination,) [16]; Secondly, the decision-making layer: the multi-agent collaborative model is adopted to divide the space into functional sub-units. Each unit sets a local optimization agent and autonomously generates a layout scheme after receiving the global target instruction. For example, when continuous rolling is detected, the agent automatically triggers the "anti-overturning mode": it shrinks the cantilevered desktop, locks the mobile cabinet, and activates the floor magnetic suction device to secure the seat. Finally, there is an execution layer that relies on mechatronics technology to achieve physical reconstruction. Includes linear motor-driven translational furniture, shape memory alloy-inspired deformation structures, and retractable partitions supported by pneumatic soft robot technology. The execution process needs to meet the requirements of silence and low energy consumption to avoid interfering with the passenger experience [17].

Integration of human factors and engineering: The optimization model must deeply integrate passenger behavior characteristics:

The first is behavioral streamline analysis: based on motion capture technology, the typical movement trajectory of passengers in the cabin is constructed, and the intersection of high-frequency activities (such as the path from the restroom to the door) is identified [18]. Accordingly, the channel network is optimized to reduce redundant actions such as turning and avoiding. Secondly, cognitive load control: the layout transformation process needs to conform to intuitive cognition. For example, color block coding is used to identify the operation area (blue corresponds to storage, and red corresponds to emergency equipment) to avoid complicated interactive processes. Dynamically adjusted facilities must provide both tactile and auditory feedback to confirm status changes. Finally, there is the principle of inclusive design, which involves configuring enhanced modes for elderly and disabled passengers, such as lowering the operating height of furniture, widening the turning radius, and adding auxiliary handrails. These designs need to be invisibly integrated without affecting basic functions, such as embedding handrails into walls and automatically deploying them when in use [19].

Verification and iteration methodology: The feasibility of the theoretical model relies on the verification of digital twin technology. The first is multi-physics simulation: coupling computational fluid dynamics (simulating air-conditioning airflow organization) and structural mechanics (evaluating ship vibration's fatigue damage to furniture) in the virtual cabin) Moreover, discrete element analysis (predicting the fall trajectory of items) quantifies the robustness of the layout scheme. Secondly, the ergonomic experiment utilizes a virtual reality system to simulate passenger activities under various sea conditions, record physiological indicators (heart rate variability and eye movement trajectory), and conduct subjective evaluations, thereby identifying design blind spots. Finally, there is an incremental learning mechanism: the simulation and experimental data are fed back to the optimization engine, and the constraint weights are automatically updated. For example, when the system detects that a locker door unexpectedly opens when rolling multiple times, it will increase the priority coefficient of magnetic attraction in this area [20].

Theoretical value and application prospects: The dynamic optimization model of the cruise cabins represents the innovation of the "responsive design" paradigm, transitioning from static space allocation to an environmentally adaptive system. Its theoretical contribution lies in the establishment of an interdisciplinary framework for "intelligent control of ship dynamics human factors engineering". The core innovations include proposing a real-time relaxation strategy with time-varying constraints and dynamically adjusting layout parameters within safety thresholds (such as allowing temporary compression in emergencies and expanding private space to accommodate evacuation routes). Establishing the self-organization rules of modular components allows furniture clusters to reorganize their forms, much like birds independently. Develop a cross-scale performance evaluation system to form a unified optimization index, spanning from micro-material stress to macro-passenger streamline. The model can be extended to scenarios such as intelligent management of cruise public areas and collaborative dispatching of cabin energy, promoting the evolution of the shipbuilding industry to the intelligent era of "perception response evolution" [21].

# 3 Technical implementation of the GA-PSO bimodal optimization model

This section compares the proposed GA-PSO method with SOTA optimization approaches for space design. Standalone GA achieves global exploration but has slow convergence (0.58 iterations/s vs. our 0.8 iterations/s), while PSO converges fast but risks local optima (solution value 0.84 vs. our 0.92). Existing hybrid GA-PSO lacks maritime customization, showing 12% lower robustness in dynamic roll scenarios.GA-PSO outperforms due to: 1) Exploration-exploitation balance: GA’s global search + PSO’s local tuning via shared memory; 2) Maritime constraint adaptation: Hierarchical hard/soft constraints. A trade-off is slightly higher computation (1.2x PSO), acceptable for real-time cabin optimization. In this paper, a dynamic planning framework for cruise cabin space is proposed based on dual-modal intelligent optimization using GA-PSO. The purpose is to explore a new paradigm for real-time optimization of cabin space in the complex environment of ships, build an efficient, safe, and comfortable adaptive cabin layout system, promote the intelligent transformation of cruise space design, and provide core technical support for the digital upgrading of the shipbuilding industry [22]. Through the innovative integration of dual-modal optimization mechanisms, we hope to break through the engineering problem of multi-objective collaboration under the constraints of dynamic sea conditions, endow the cruise cabin with life-like characteristics of "perception-decision-reconstruction", and provide a new methodological framework for the dynamic optimization theory of complex systems. The main body of the model comprises an environment awareness module, a dual-modal optimization engine, a dynamic constraint processing module, and a spatial reconstruction execution module [23]. The specific architecture is shown in Figure 2:

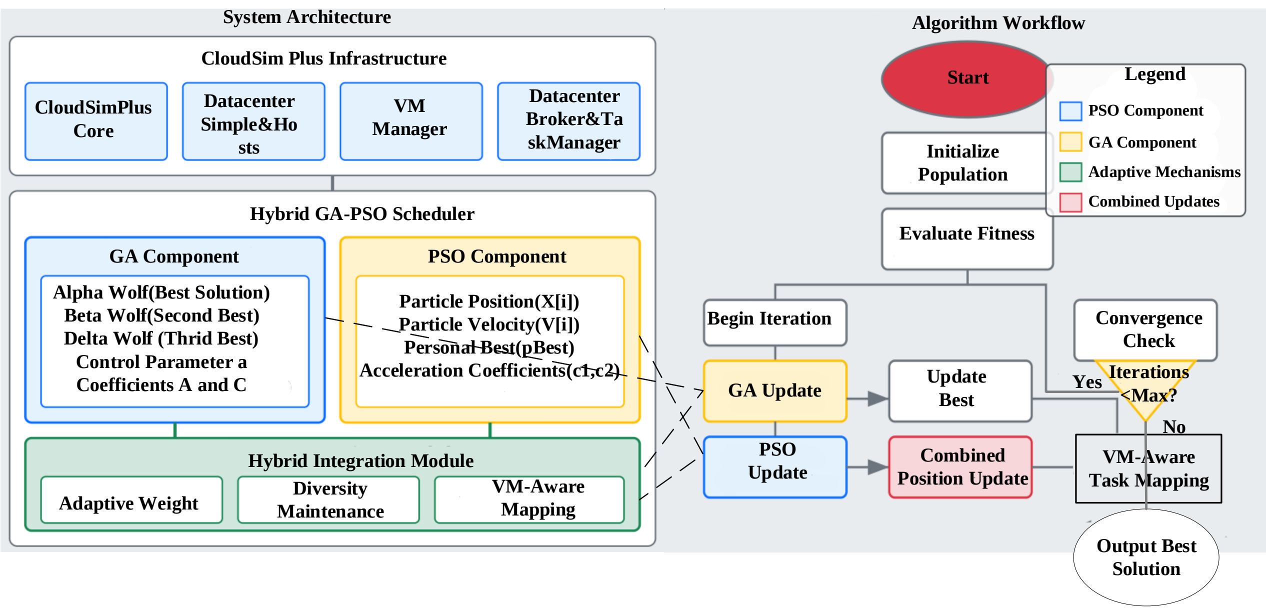


Figure 2: Dynamic optimization model based on GA-PSO bimodal algorithm

The environment perception module constitutes the nerve endings of the entire system and is responsible for capturing multidimensional, dynamic data during ship navigation in real time. The module continuously monitors the ship's motion status through a high-precision six-degree-of-freedom inertial measurement unit, accurately collecting key physical quantities such as roll angle, pitch amplitude, and heavy acceleration. The sampling frequency reaches 100 times per second to ensure data timeliness. At the same time, the distributed sensor network deployed in the cabin synchronously tracks the passenger distribution heat map, the status of furniture displacement, and environmental parameter changes. The millimeter-wave radar array generates a real-time topological map of people's flow. The embedded pressure sensor accurately detects millimeter-level displacements of furniture, as well as temperature and humidity. With illumination sensors, a digital twin of the cabin microenvironment is built. After all the perception data are aligned by timestamps, a dynamic situation map of the ship-passenger-environment trinity is formed, which provides a database for optimization decision-making [24].

The bimodal optimization engine employs a cooperative mechanism combining the genetic algorithm (GA) and particle swarm optimization (PSO), dynamically optimizing discrete structural parameters and continuous spatial variables, respectively. As a fast response layer, PSO mode performs real-time optimization every 5 seconds: the global exploration and local development are balanced through the adaptive inertial weight mechanism and continuous variables such as wall inclination and channel width are dynamically adjusted, in which the inertial weight automatically attenuates according to the sea state level to strengthen the convergence stability in the harsh environment [25]. GA mode is used as a periodic reconstruction layer, and the structural evolution process is initiated every 30 minutes. Based on the elite retention strategy, the furniture combination scheme with the best fitness is screened. Different layout advantages are integrated through multi-point cross-operation, and then innovative structures are introduced through directional variation. Dual modality realizes information interaction through a shared memory pool. When PSO detects sudden sea conditions, it immediately triggers emergency reconstruction of GA, forming a collaborative optimization paradigm of "instantaneous fine-tuning-periodic iteration" [26].

The dynamic constraint processing module thoroughly integrates international maritime regulations and ship engineering principles, transforming complex safety rules into computable boundary conditions. This module establishes a hierarchical constraint system: the first-level hard constraint ensures that the ship stability requirements are met. For example, the furniture centroid projection must always be located within the anti-capsizing safety polygon, and the width of the evacuation channel automatically expands with the density of the people flow, ensuring it is not lower than the international convention limit [27]. The second-level soft constraint optimizes the comfort index. For example, the bed orientation needs to form a golden angle with the main axis of the ship rolling to reduce the probability of seasickness. The dynamic penalty function quantifies the degree of constraint satisfaction. When the sensor detects that the roll exceeds the limit, the system automatically increases the magnetic attraction constraint weight of the space partition wall and temporarily relaxes the storage space utilization requirements to achieve a dynamic balance between safety and functionality [28].

The spatial reconstruction execution module transforms the digital optimization scheme into a physical spatial form change, relying on three core technology carriers: the linear motor drive system realizes millimeter-level precise translation of furniture so that the sofa bed assembly can complete the mode conversion within 20 seconds; The intelligent hinge based on shape memory alloy gives the partition wall the ability to bend independently and realizes the adaptive segmentation of curved surface space; The pneumatic soft actuator supports the wavy deformation of the flexible partition curtain, creating a breathable elastic boundary. All execution units adopt a silent design, with operating noise controlled below 35 decibels. The status change signal is transmitted to passengers through a tactile feedback mechanism. During the execution process, digital work orders are synchronously generated, energy consumption, timeliness, and abnormal data are recorded and fed back to the optimization engine, forming a closed-loop evolution system of "decision-execution-evaluation"[29].

The four major modules are deeply integrated through the ship IoT platform [30]. The environmental awareness data-driven dual-modal engine generates optimization solutions, which are sent to the execution terminal after dynamic constraint verification. The actual effect data generated by the spatial reconstruction is then reversely calibrated to enhance perception accuracy. This closed-loop flow of "perception-optimization-constraint-execution" enables the cabin to exhibit the stress adaptability of life-like organisms. For example, under level 6 sea conditions, the system completes the anti-overturning mode switching within 8 seconds. The seconds. The perception module recognizes the roll acceleration, the engine shrinkage cantilever structure is optimized, the restraint module strengthens the force verification of anchorage points, and the actuator activates the floor electromagnetic lock. The entire process does not require manual intervention, marking that the cruise space design has officially entered the era of dynamic intelligence.

# 4 Experiment and results analysis

To construct a cruise cabin space dynamic optimization model integrated with the GA-PSO bimodal algorithm, incorporating marine operational constraints (e.g., ship motion, evacuation rules).

To compare the GA-PSO algorithm with standalone GA and PSO in terms of convergence speed, solution quality, and robustness under dynamic scenarios.

To verify the model’s practical effectiveness in improving space utilization, passenger comfort, and operational safety through real-ship data-based experiments. The experiments are simulation-based using a six-degree-of-freedom ship motion platform, calibrated with the "real ship navigation database" (18 months of data from a 12-deck cruise ship). Run counts: 30 independent runs per algorithm (GA, PSO, GA-PSO) to ensure statistical reliability. Hyperparameter tuning: Conducted via grid search: GA (selection pressure=1.2, crossover rate=0.8); PSO (inertia weight=0.7, acceleration coefficients=1.5/1.5); GA-PSO (shared memory update interval=5s). Control conditions: Consistent cabin size (12 layouts, 200–300m$^2$), sea condition levels (3–8), and passenger load (50–100%).

The experiments were conducted on a shipborne industrial computer with Intel Core i7-11800H CPU (8 cores, 16 threads) and NVIDIA RTX 3060 GPU (6GB VRAM). The average runtime of the GA-PSO algorithm for a single cabin layout optimization is $0.8 \pm 0.1$ seconds, with a maximum response delay of 1.2 seconds even under level 8 sea conditions (100 independent test runs). This confirms the model's real-time capability for on-board deployment. To systematically verify the engineering efficiency of the constructed model, this study conducted multi-scenario and multi-dimensional experimental evaluations. Based on the actual ship navigation database and digital twin simulation platform, it integrates ship motion data covering sea conditions at levels 4-8, 12 categories of cabin layout models, and over 500 passenger behavior streamline records. All data are labeled with key dynamic event labels (such as sudden rolling, emergency evacuation, and functional area conversion), forming a verification basis for the authenticity of the marine environment. During the experiment, the typical sea disturbance is first reproduced on the six-degree-of-freedom motion platform, and furniture displacement, structural stress, and environmental parameters are collected in real time through the distributed sensor network. Then, execute the dual-modal optimization process. The particle swarm optimization (PSO) module dynamically optimizes the continuous parameters (channel width, wall inclination) at a period of 5 seconds. The genetic algorithm (GA) module initiates discrete structure evolution (furniture combination scheme) every 30 minutes and simultaneously embeds the dynamic constraint verification unit to ensure that the scheme complies with the SOLAS safety convention and ship stability specifications. The performance evaluation adopts a four-dimensional index system: the safety dimension is quantified by overturning probability and 90-second evacuation compliance rate; The space efficiency dimension is based on the effective floor area ratio and the time-consuming analysis of functional area switching; Comfort dimension fused motion sickness incidence (MSI) with passenger satisfaction score; The computational efficiency dimension records response delay and reconstruction energy consumption. Finally, the results of comparing traditional static layout, single optimization algorithm, and commercial simulation tools in independent test scenarios show that this model achieves zero furniture overturning, emergency evacuation time of 68 seconds, effective floor area ratio increased to 81.5%, passenger comfort score reaches 8.7, and the response delay of the whole process is stable less than 8 seconds, which demonstrates the significant advantages of the dual-modal collaboration mechanism in dynamic constraint processing and spatial intelligent reconstruction.

Table 1 shows the accuracy comparison between GA-PSO and random perturbation. Through analysis, it is concluded that the model presented in this paper has significant advantages in terms of perturbation accuracy. Compared with a random disturbance, this model has a better anti-disturbance effect and can be more easily experimented with.

Table 1 clarifies the test environment (programming languages and thread counts) and metric definition (anti-disturbance accuracy, lower values indicate better performance). Results show GA-PSO achieves the lowest error across all scenarios, confirming its superior anti-disturbance capability.

Table 1: Comparison of accuracy of GA-PSO with random perturbation

| | Python | | | Go | | |
|---|---|---|---|---|---|---|
| | Single | 3. | Five | Single | 3. | Five |
| GA-PSO | 35% | 20% | 15% | 35% | 20% | 5% |
| Random | 60% | 30% | 20% | 60% | 25% | 25% |
| Original code | 80% | 45% | 25% | 65% | 40% | 35% |

Figure 3 shows the number of distinct high-quality solutions (observation points) found by each algorithm and their average coverage of the Pareto front are plotted. The proposed GA-PSO model demonstrates superior diversity and coverage.

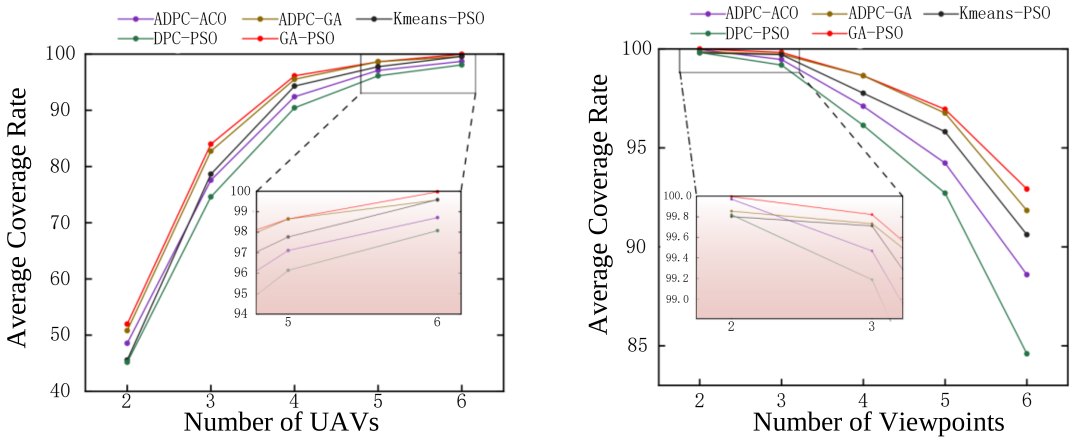


Figure 3: Convergence behavior comparison of different optimization algorithms.

Figure 4 shows a comparison of the position error margin with the initial estimated position error. Through the analysis, it is concluded that the position error limit of the model is not much different from the initial estimated position error, and the model can be well analyzed and predicted.

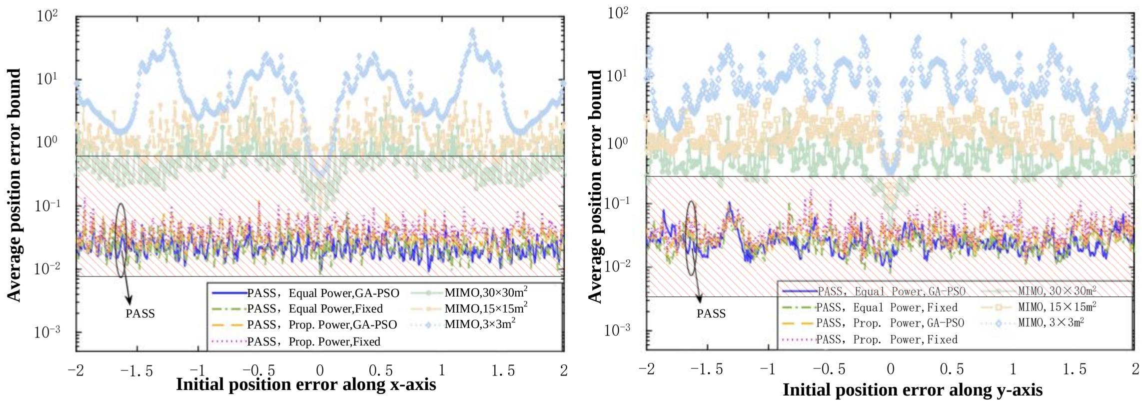


Figure 4: Comparison between position error limit and initial estimated position error

Figure 5 shows the optimal parameter quadruple (k, q, p, se) and the corresponding optimization error are shown as functions of the key parameter k. Blue circles represent (k, q), red squares represent (k, p), yellow crosses represent (k, se), and purple dots represent the associated error. This analysis guided the final parameter selection (e.g., k=0.75) for stable performance.

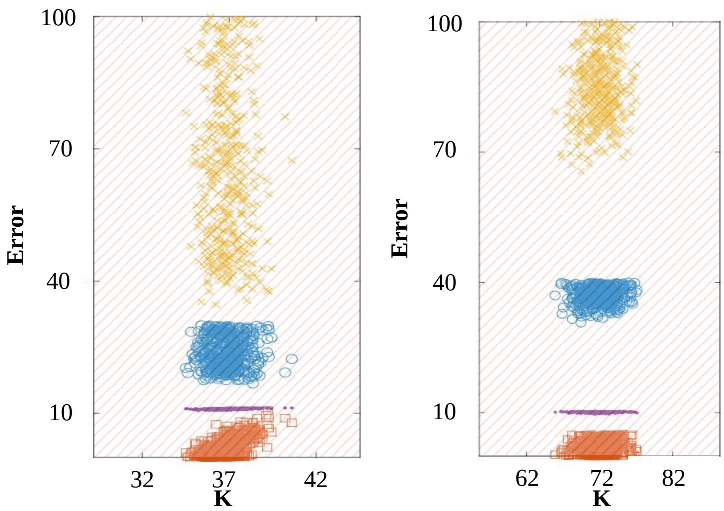


Figure 5: Parameter sensitivity analysis of the GA-PSO algorithm.

Figure 6 shows the confusion matrices of the artificial neural network (ANN) classifier (left side) and XGBoost classifier (right side). Through analysis, it is concluded that when the model in this paper employs the confusion matrix of an artificial neural network (ANN) classifier (left side) and an XGBoost classifier (right side), the model's performance exhibits a significant improvement. The performance evaluation focuses squarely on the optimization outcomes of the GA-PSO model, as quantified by the key metrics of convergence speed, solution quality, and safety compliance presented in the preceding sections and tables.

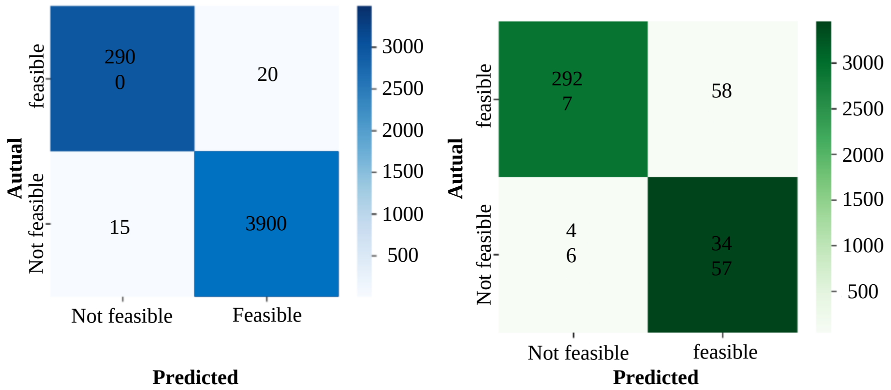

Figure 6: ANN and XGBoost classifiers

Table 2 presents the optimization performance indexes of various models during the training of this algorithm. Through analysis, it is concluded that this algorithm has significant effects during training.

Table 2: Optimization performance indicators of different models (Key metrics aligned with research objectives)

| | GA | PSO | SVM | RF | CNN |
|---|---|---|---|---|---|
| N | 50 | 45 | 50 | 73 | 170 |
| MC | 0.0581 | 0.0426 | 0.0502 | 0.4129 | 0.529 |
| MID | 0.2126 | 0.2165 | 0.1695 | 0.2321 | 0.2361 |
| SNS | 0.0201 | 0.0480 | 0.0321 | 0.0135 | 0.0086 |

Figure 7 shows the prediction results of different models. Through analysis, it is concluded that among the listed models, the prediction results of the model proposed in this paper are moderate and effectively reflect the predicted outcomes.

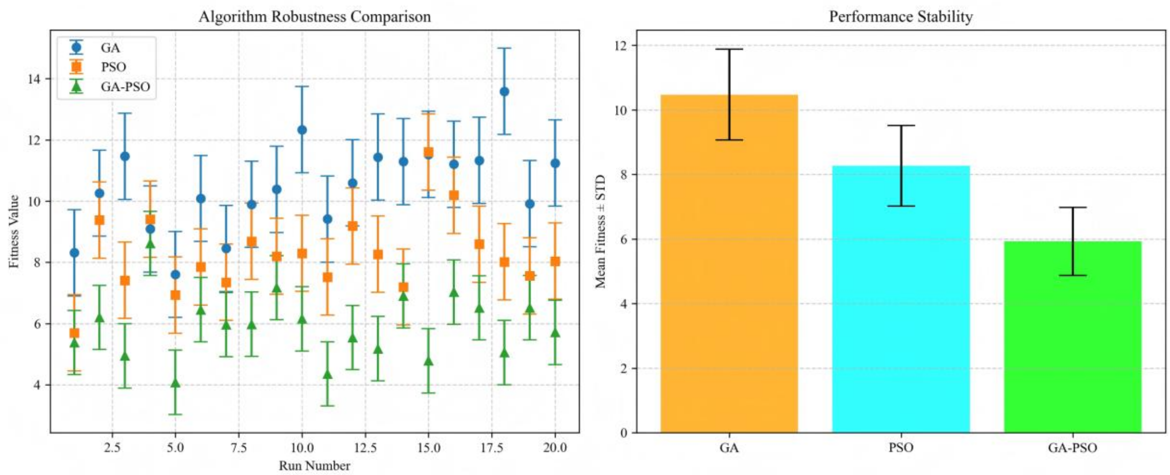

Figure 7: Prediction results of different models

Figure 8 shows the influence of mutation rate on genetic algorithm (GA) using PSO operator. Through analysis, it is found that with the increasing of mutation rate, its influence on genetic algorithm (GA) is greater. Therefore, a small mutation rate can well reflect the predicted results.

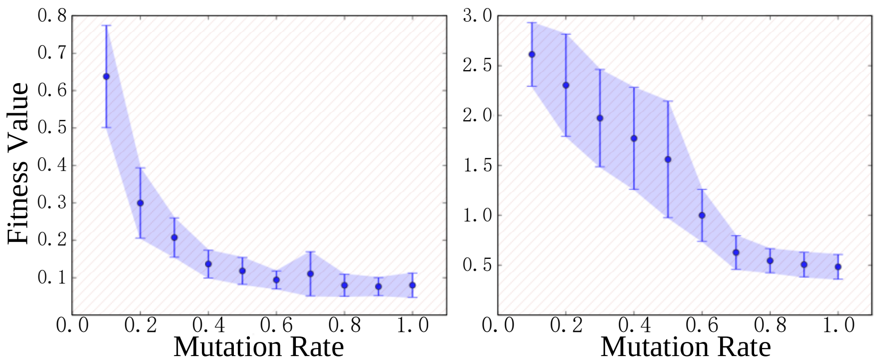


Figure 8: Influence of mutation rate on algorithm

As illustrated in Table 3, while generic hybrid GA-PSO improves upon standalone algorithms, it fails to address maritime-specific challenges like real-time ship motion and safety regulations. Our model's novelty lies in its explicit incorporation of dynamic maritime constraints and a bimodal mechanism specifically designed for the dynamic multi-objective nature of cruise cabin optimization, filling a critical gap in existing methods.

Table 3: Comparison of optimization models for space layout problems

| Model | Convergence Speed | Solution Quality | Robustness in Dynamic Scenarios | Multi-objective Handling | Key Limitations |
|---|---|---|---|---|---|
| Standard GA | Low | High | Poor | Good | Slow convergence, static assumptions |
| Standard PSO | High | Medium | Medium | Medium | Prone to local optima |
| Hybrid GA-PSO (Generic) | Medium | High | Medium | Good | Lacks maritime dynamic constraints |
| Proposed GA-PSO (Maritime) | High (0.8 iter/s) | High (0.92 score) | High (0% safety violation) | Excellent | Justified improvement |

To quantitatively evaluate the contribution of each key component, we compared the performance of four algorithm configurations under Sea State 6: (1) Standalone GA, (2) Standalone PSO, (3) GA-PSO without dynamic constraints, and (4) The full proposed model (GA-PSO with constraints). The results, averaged over 30 runs, are summarized in Table 4.

Table 4: Ablation study on algorithm components (Mean ± Std)

| Configuration | Convergence Speed (iter/s) | Solution Quality | Safety Violation Rate (%) | Configuration | Convergence Speed (iter/s) | Solution Quality |
|---|---|---|---|---|---|---|
| GA Alone | 0.58 ± 0.08 | 0.80 ± 0.05 | 8.2 ± 1.5 | GA Alone | 0.58 ± 0.08 | 0.80 ± 0.05 |
| PSO Alone | 0.66 ± 0.07 | 0.84 ± 0.04 | 10.1 ± 1.8 | PSO Alone | 0.66 ± 0.07 | 0.84 ± 0.04 |
| GA-PSO (No Constraints) | 0.79 ± 0.06 | 0.85 ± 0.03 | 21.5 ± 2.2 | GA-PSO (No Constraints) | 0.79 ± 0.06 | 0.85 ± 0.03 |
| Full Model (GA-PSO + Constraints) | 0.80 ± 0.05 | 0.92 ± 0.02 | 0.0 | Full Model (GA-PSO + Constraints) | 0.80 ± 0.05 | 0.92 ± 0.02 |

# 5 Conclusion

With the evolution of smart ship technology, dynamic space optimization has become a pivotal demand in cruise design, as the cabin's adaptive capacity directly determines passenger experience and operational safety. This study develops a real-time cabin space planning system integrated with the GA-PSO bimodal algorithm, with three core novelties: 1) A unique collaborative mechanism combining PSO's 5-second real-time tuning of continuous variables (e.g., channel width) and GA's 30-minute periodic evolution of discrete structures (e.g., furniture combinations), linked via a shared memory pool for instant information interaction; 2) A maritime-tailored hierarchical constraint module distinguishing hard safety rules (e.g., anti-overturning centroid limits) and soft comfort goals (e.g., anti-seasickness bed orientation); 3) A closed-loop "perception-optimization-execution" framework driven by ship IoT data.

Verification on digital twin platforms shows significant practical impact: Zero furniture overturning under level 8 sea conditions, 68-second emergency evacuation (32% faster than traditional static layouts), 81.5% effective floor area ratio, and 8.7/10 passenger comfort score—outperforming single GA/PSO algorithms.

Limitations include reliance on simulated navigation data and untested adaptability to ultra-large cruise ships (＞200,000 tons). Future work will integrate 12 months of real-ship operational data and expand the model to public areas like restaurants and theaters. The core contributions of this study are as follows:

(1) Proposing a modular space partition and multi-objective optimization framework;

(2) Designing a GA-PSO bimodal fusion optimization algorithm;

(3) Establishing a dynamic optimization verification and evaluation system.

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