# An Intelligent Ship Equipment Layout Design Method Based on the AEPSO Algorithm and Multiple Optimization Strategies

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**Abstract.** To address the limitations in ship equipment layout design (SELD), such as excessive reliance on expert experience, poor adaptability of traditional optimization algorithms, and susceptibility to local optima, this study proposes an intelligent layout method that integrates an adaptive enhanced particle swarm optimization (AEPSO) algorithm with multiple adaptive strategies. The approach introduces a dynamic parameter adjustment mechanism to improve global search performance, while incorporating particle scouting and mutation elimination strategies to enhance local exploitation and global exploration capabilities, thereby improving both solution quality and diversity. The layout model comprehensively considers equipment interrelations, zone feasibility, spatial constraints, and engineering rules, and employs a multi-objective evaluation function covering key indicators such as collaboration, space utilization, and layout stability. Finally, the method is validated through a real-world ship engine room case study. Experimental results demonstrate that the proposed method outperforms the standard PSO in convergence speed, optimization accuracy, and adaptability, with improvements of 3.5% and 12.6% in accuracy and speed, respectively. Compared to expert-designed layouts, the proposed method yields over 6.9% improvement, validating its effectiveness and practical value in addressing complex layout challenges. This method holds promise as an intelligent optimization solution for preliminary ship design.

**Keywords:** Ship Equipment Layout Design；PSO algorithm；Adaptive Optimization Strategy；Automation design.

## 1. Introduction

With the acceleration of global economic integration, maritime transport now carries over 80% of international cargo, driving ship design toward greater size, intelligence, and environmental sustainability. As a core subsystem, the engine room layout directly impacts ship safety, energy efficiency, and maintainability. SELD must meet complex functional and spatial constraints through multi-objective optimization[1]. The piping system, as the interconnection among equipment, further increases spatial coupling and design complexity, making SELD a high-dimensional, strongly constrained problem requiring both global coordination and local precision. However, current practices still rely heavily on manual trial-and-error and expert experience, leading to inefficiencies. Existing automated methods often neglect inter-equipment dependencies, limiting their applicability. Therefore, a practical, intelligent SELD optimization method is urgently needed to enhance design quality and efficiency and support next-generation ship design.

### 1.1 Related research of SELD

The study of SELD began in the mid-20th century, initially focusing on basic geometric modeling and linear programming to address fundamental issues of spatial utilization and equipment arrangement. With the increasing complexity and automation of ship systems, research has gradually shifted toward the integration of 3D spatial modeling, multi-objective optimization, and intelligent algorithms. Currently, SELD research mainly follows two paths: (1) intelligent optimization method based on heuristic and metaheuristic algorithms, and (2) semi-automated layout strategies incorporating human-computer collaboration.

Extensive efforts have been made in this domain. For example, Meng et al.[4] introduced human reliability analysis (HRA) to improve safety and operability evaluation in layout design. Lee[5] proposed a method combining the Modified Iterative Deepening Search (MIDS) algorithm with a greedy strategy, showing strong adaptability and convergence in complex offshore environments. Wang et al.[2] proposed a knowledge-based design framework for 3D cabin equipment layout optimization. Li et al.[6] developed a two-stage optimization model combining NSGA-II and hybrid bin-packing strategies to address complex constraints in engine room layout. Zhang et al.[7] proposed a bidirectional co-optimization method for simultaneous layout of equipment and piping systems in ship engine rooms. Despite the progress made in optimization efficiency and algorithm adaptability, traditional methods still face significant challenges when applied to high-dimensional, multi-objective, and strongly constrained 3D equipment co-layout tasks. These challenges include limited search capability, reduced convergence efficiency, and insufficient solution stability. Therefore, it is imperative to develop a more generalizable and adaptive SELD optimization method by innovating at both the algorithmic and modeling levels.

### 1.2 Related research of PSO

Since the introduction of PSO by Kennedy and Eberhart in 1995[8], the algorithm has gained wide application across domains such as power systems, mechanical design, bioinformatics, and intelligent manufacturing, owing to its simplicity, flexible parameters, and fast convergence. Its core mechanism mimics bird foraging behavior, enabling efficient global search through individual-swarm information sharing.

In engineering applications, Yoshida et al. [9] applied PSO to reactive power and voltage control in power systems; Abido[10] employed it for designing power system stabilizers; Eberhart et al.[11] used PSO to optimize neural network weights for Parkinson's disease diagnosis; Sun et al.[12] combined GA-PSO-BP neural networks for housing price prediction. Tan et al.[13] demonstrated PSO's superior convergence in handling nonlinear, multi-variable, and constrained problems compared to genetic algorithms and ant colony optimization. In ship design, PSO has shown notable effectiveness: Du et al.[14] optimized marine energy management strategies using improved PSO; Nazemian et al.[15] integrated PSO with CFD and adjoint solvers for trimaran hull optimization; Zhang et al.[16] used PSO for optimizing bulbous bow shapes, achieving drag reduction through CFD simulations.

In summary, PSO offers strong global search capability, parallelism, and flexibility, making it highly suitable for complex engineering layout problems such as SELD. However, due to the high dimensionality, complex coupling, and multi-constraint nature of SELD tasks, standard PSO often struggles with convergence and search depth. To address these limitations, this study develops an AEPSO-based optimization framework that integrates multiple efficient strategies. The aim is to enhance the algorithm's intelligence, robustness, and global optimization performance for handling complex collaborative layout challenges in ship design.

## 2. SELD formulation

### 2.1 Spatial parameterization and layout principles

Engine rooms host diverse equipment with varying spatial and functional requirements related to energy access, space occupation, and thermal constraints. SELD aims to optimize the spatial layout while satisfying engineering standards. As shown in Fig. 1, the layout is modeled using a 3D Cartesian coordinate system, with each device represented by a center point ($x_c$, $y_c$, $z_c$) and a rectangular bounding box defined by diagonal corners ($X_{\min}$, $Y_{\min}$, $Z_{\min}$) and ($X_{\max}$, $Y_{\max}$, $Z_{\max}$). This standardized parameterization supports obstacle detection and constraint enforcement[17]. Key layout elements—including equipment bodies, energy zones, and pipe nozzles—are described in 3D to ensure model consistency. Engineering constraints such as spatial safety, functional relevance, and maintenance access are formulated mathematically. The space is further divided into restrictive zones (e.g., obstacles, high-risk areas) and guiding zones (e.g., along bulkheads or near fixed equipment), enabling more precise constraint modeling. In essence, SELD is a nonlinear, multi-objective problem requiring accurate geometric abstraction to serve as input for intelligent optimization.

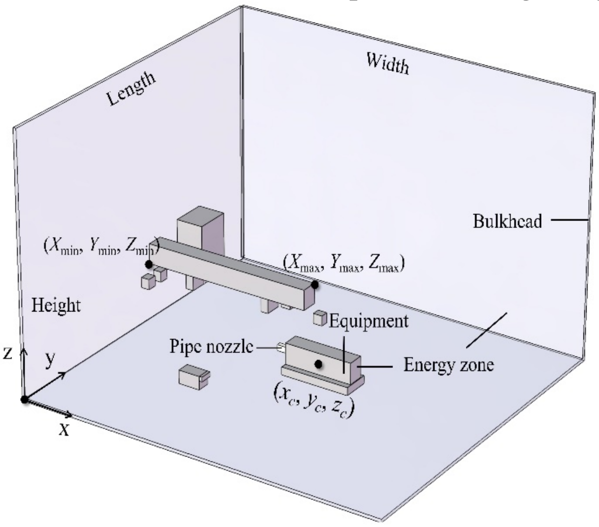


Fig. 1. Schematic diagram of parameterized analysis for the SELD problem

$$S_i = \{e_1, e_2, \cdots, e_n\}, e_i = (x_i, y_i, z_i) \tag{1}$$

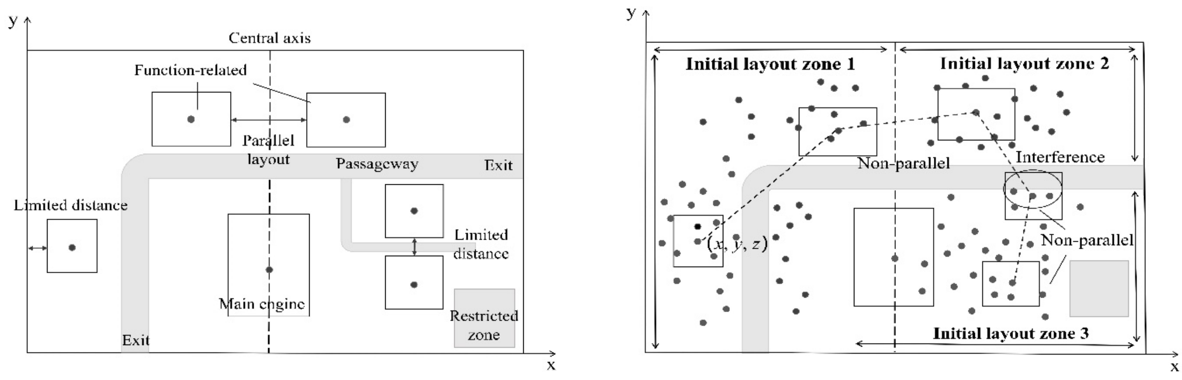


Fig. 2. Principle of equipment coding expression (a) Layout constraints (b) Initial vector points.

### 2.2 Coding method and mathematical expression

To facilitate subsequent algorithmic processing, equipment positions need to be digitally represented. The initial placement of the equipment cannot be entirely random; it must comply with basic spatial constraints and functional requirements. As discussed in Section 1.1, many studies have incorporated actual engine room environments and expert knowledge to preliminarily define feasible layout zones[6]. Fig. 2(a) illustrates a standard equipment layout, including passageway location, functional requirements, spacing constraints, and restricted zone. As shown in Fig. 2(b), based on real engine room configurations, this study partitions the equipment placement space into multiple initial feasible layout zones. Each piece of equipment is represented by a position vector ($x_i$, $y_i$, $z_i$) within its designated zone, forming an initial population. Each set of vectors represents a group of candidate schemes for the equipment (as illustrated by the dashed-line in the figure). To improve algorithmic efficiency, this study constructs layout scheme paths by sequentially combining equipment center positions, as shown in Equation (1). Based on this, the corresponding objective values are iteratively optimized to identify the optimal layout solution. This method balances spatial feasibility and computational simplicity, making it well-suited for complex compartment equipment layout tasks.

### 2.3 Constraints and evaluation function

Before executing the optimization algorithm, an appropriate evaluation function must be defined to guide the search direction. A scientifically grounded evaluation mechanism is fundamental to achieving a high-quality layout. In the SELD domain, a relatively mature assessment system has been established and widely validated in prior studies [2][7][18]. To ensure the accuracy and reliability of this study, a set of objectives and constraints is formulated based on an established evaluation framework, while incorporating the specific characteristics of the layout problem: (1) Objective 1 (Equation 2): Minimize equipment torque imbalance. To maintain force equilibrium on both sides of the main engine axis, the rotational moment generated by equipment must be minimized. (2) Objective 2 (Equation 3): Enhance functional collaboration and operational safety. Functionally related equipment should be placed in proximity to improve system response efficiency and operational reliability. Additionally, to facilitate emergency evacuation, the distance between equipment and exits should be minimized. (3) Objective 3: Improve piping layout efficiency. While optimizing equipment positions, the connectivity and convenience of subsequent pipe layouts should also be considered. This objective can be integrated into the distance term of $f_2(e\_s)$ for unified evaluation.

$$f_1(e\_s)=\sum_{i=1}^{N}G_i\left(y_i-\frac{W}{2}\right) \tag{2}$$

where $G_i$ denotes the weight of equipment $i$, and $W$ is the width of the engine room.

$$f_2(e\_s)=\sum_{i,j}^{N}D_{ij}\times\tau_{ij}+\varphi\times\sum_{i}S_i \tag{3}$$

where $D_{ij}$ indicates the distance between equipment $i$ and $j$ (measured by interface or center point). $\tau_{ij}\in[0,1]$ is the functional relevance weight. $S_i$ represents the distance from equipment $i$ to the nearest exit, and $\varphi\in[0.1,0.5]$ denotes the safety sensitivity factor.

In addition, to ensure the feasibility of the layout solutions, the following constraint function $f_3(e\_s)$ is introduced, which includes: Equation (4): Collision and interference detection between equipment; Equation (5): Minimum safety distance between equipment, and between equipment and bulkheads; Equation (6): Parallel layout requirement for functionally or volumetrically equivalent equipment. The specific modeling principles are based on [18].

$$P_1(e\_s)\rightarrow\left\{E_i\cap E_j\,\middle|\,\forall i,j\in N,i\neq j\right\} \tag{4}$$

$$P_2(e\_s)\rightarrow\left\{\left\{\left|E_{ic}-E_{jc}\right|>D\right\}\cap\left\{\left|E_{ic}-H_c\right|>D\right\}\middle|\forall i,j\in N,i\neq j,c=(x,y,z)\right\} \tag{5}$$

$$P_3(e\_s)\rightarrow\left\{E_{ix}=E_{jx}\cup E_{iy}=E_{jy}\cup E_{iz}=E_{jz}\,\middle|\,V_i=V_j,\forall i,j\in N,i\neq j\right\} \tag{6}$$

Based on the objectives and constraints defined above, the evaluation function for equipment layout is formulated as follows:

$$\min F(e\_s)=s_1\times\min f_1(e\_s)+s_2\times\min f_2(e\_s)+s_3\times\min f_3(e\_s) \tag{7}$$

where $F(e\_s)$ follows the minimization-based approach proposed in [6]. Considering that the dimensionality and complexity of this layout problem are comparable to those in the reference, the weighting coefficients are normalized accordingly. The final weights assigned to the evaluation sub-functions are set as: $s_1 = 0.02$, $s_2 = 0.78$, and $s_3 = 0.2$.

# 3. Equipment layout method based on improved AEPSO

## 3.1 Fundamental principle of PSO

PSO models each candidate solution as a particle moving through the search space, with its position representing a solution and velocity determining movement. Particle updates are guided by two key metrics: personal best (*pbest*) and global best (*gbest*), which reduce randomness and enhance convergence. Through iterative updates, particles adjust their positions based on *pbest* and *gbest*, gradually approaching optimal regions. Upon meeting termination criteria (e.g., maximum iterations or convergence), *gbest* is taken as the approximate global optimum. The core of PSO lies in its velocity and position update mechanism (Equation (8)). Unlike traditional evolutionary algorithms, PSO avoids complex operations like crossover or mutation, relying instead on collective learning and information sharing among particles. This endows PSO with strong global search capability and robustness.

$$\begin{cases} v_i^{t+1} = w \times v_i^t + c_1 \times r_1 \times (pbest_i - x_i^t) + c_2 \times r_2 \times (gbest - x_i^t) \\ x_i^{t+1} = x_i^t + v_i^{t+1} \end{cases} \tag{8}$$

where $v_i^t$ and $x_i^t$ are the velocity and position vectors of particle *i* at iteration *t*. $w$ is the inertia weight (balancing exploration and exploitation). $c_1$, $c_2$ are cognitive and social learning factors. $r_1$, $r_2$ are random values in [0, 1]. $pbest_i$ is the best position found by particle *i*, and *gbest* is the best across the swarm.

### 3.2 Principle of the improved AEPSO

Although the standard PSO demonstrates strong global search capability and convergence in continuous optimization problems, it often suffers from premature convergence and loss of population diversity when dealing with high-dimensional, multi-constraint, and complex problems. To address these limitations, this study proposes an Adaptive Enhanced algorithm AEPSO. AEPSO incorporates three strategies to enhance both global exploration and local exploitation, thereby improving solution quality and stability in complex SELD tasks.

(1) Parameter adaptive strategy

In ship equipment layout optimization tasks, the algorithm must maintain a dynamic balance between global exploration and local refinement. To achieve this, an adaptive inertia weight strategy is adopted, where the inertia weight *w* is dynamically adjusted according to a linear decreasing function:

$$w = \left(w_{\max} - w_{\min}\right) \times \left(1 - t/T\right) + w_{\min} \tag{9}$$

where $w_{\max}$ and $w_{\min}$ are the upper and lower bounds of inertia weight *w*. t and T denote the current and maximum iterations.

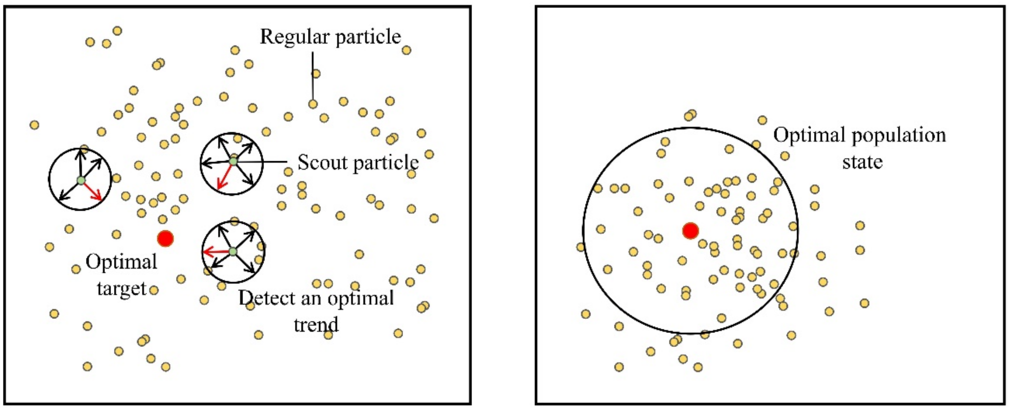
This mechanism enhances the algorithm's global search capability in the early stages, facilitating comprehensive exploration of the layout space and avoiding premature convergence to local optima. In later iterations, the decreasing weight helps focus on the neighborhood of promising solutions, thereby refining local adjustments and improving layout precision. To further strengthen the algorithm's ability to escape local optima, an adaptive mutation rate mechanism is introduced. When no better solution is found over several consecutive generations, the algorithm is considered to be trapped in a local optimum. In such cases, the mutation probability mmm is increased to guide the search out of stagnation. The update rule is defined as follows:

$$m = \min\left(m_{\min} \times (1+C_{\text{local}}),\, m_{\max}\right) \tag{10}$$

where $m_{\min}$ and $m_{\max}$ are the minimum and maximum mutation rates, respectively (set to 0.3 and 0.7 in this study), $C_{\text{local}}$ is the number of consecutive stagnation iterations.

This mechanism works in conjunction with the mutation-elimination strategy proposed in Section (3). When the search process stagnates, Gaussian perturbations are introduced to reconstruct and optimize a subset of particles. This not only enhances solution diversity but also improves the model's adaptability to highly constrained spaces, thereby boosting overall search efficiency and solution quality.

(2) Particle scouting strategy




(b)

Fig. 3. Illustration of the particle scouting strategy (a) Initial exploration state (b) Optimal population state.

To enhance the algorithm's ability to escape local optima and maintain search efficiency, a particle scouting strategy is introduced. By designing particles with "scouting behavior," the algorithm enables proactive exploration of regions far from the current solution set, thereby facilitating deeper global exploration of the layout space. As illustrated in Fig. 3, certain scouting particles, after multiple random explorations, discover a more promising direction (e.g., the red arrow), effectively guiding the entire swarm toward the global optimum. This strategy activates the random scouting process for a subset of particles with a certain probability $p$ (set to approximately 0.3 in this study). Each selected particle performs random directional moves within its current search region. The candidate solution $x_i$ generated at each move is defined by the following equation:

$$\tilde{x}_i = x_i + w \cdot v_i + c_2 \cdot r \cdot (gbest - x_i) \quad (11)$$

If the candidate position yields a better fitness value than the current one, the particle updates its position and velocity toward the new direction:

$$\begin{cases} v_i^{\text{new}} = w \cdot v_i + c_1 \cdot r_1 \cdot \dfrac{(\tilde{x}_i - x_i)}{\| \tilde{x}_i - x_i \|} + c_2 \cdot r_2 \cdot (gbest - x_i) \\ x_i^{\text{new}} = x_i + v_i^{\text{new}} \end{cases} \quad (12)$$

Moreover, to ensure the physical feasibility of the particle scouting process, each position update must satisfy boundary constraints. During scouting, the three-dimensional coordinates ($x$, $y$, $z$) of the equipment are strictly confined within the predefined feasible spatial boundaries. This strategy integrates both individual and global experience to introduce diversity during exploration, effectively mitigating premature convergence. Compared to traditional PSO's blind iteration, the AEPSO enables selective global exploration, improving convergence quality and engineering applicability. It is particularly suitable for multi-constrained SELD tasks.

(3) Mutation-elimination strategy

To mitigate premature convergence and stagnation, an elite-guided mutation-elimination strategy is introduced into the standard PSO framework. This approach integrates Gaussian perturbation with an adaptive mutation probability to enhance population diversity while preserving solution quality. The key steps are as follows：

(1) The population is ranked based on fitness. The top 10% of individuals are selected as the elite pool for mutation sources, while the bottom 5% are marked as candidates for elimination.
(2) For each low-quality individual, a solution is randomly sampled from the elite pool and modified by a Gaussian perturbation to generate a new candidate, as defined in Equation (13).
(3) The newly generated solution replaces the original inferior one, and its fitness is re-evaluated.
(4) The best individual in the updated population is compared with the current global best; if superior, it replaces the global best.

$$x_j' = x_j + \sigma \times N(0,1) \quad (13)$$

where $\sigma$ is the scaling factor that controls the magnitude of the perturbation. It is defined as $\sigma \sim U(5,10) \times P_{\mathrm{mut}}$, $P_{\mathrm{mut}}$ is the adaptive mutation probability governed by the number of stagnant generations in optimization (see Section 3.2.1).

This strategy guides inferior solutions toward superior ones while preserving elite individuals. Compared to blind random mutations, it offers stronger convergence and search efficiency, effectively mitigating premature convergence issues in highly constrained solution spaces.

### 3.3 Equipment layout optimization method based on AEPSO

Based on the proposed adaptive parameter, particle scouting, and mutation-elimination strategies, a complete AEPSO-based equipment layout optimization framework is developed. The overall process is illustrated in Fig. 4, and the steps are as follows:

Step 1: Divide layout zones and set parameters. The layout space is partitioned according to [6], considering geometry, equipment attributes, and engineering constraints to ensure balanced distribution. PSO parameters and control variables are then initialized.

Step 2: Initialize particle positions and the global best evaluation value *E_v*. The initial swarm, representing multiple candidate layout solutions for the equipment, is generated and evaluated. The evaluation value of the current globally best layout is then selected as the initial *E_v*.

Step 3: Update velocity and position with adaptive parameters. Each particle updates its velocity and position using the adaptive inertia weight mechanism, balancing global exploration and local exploitation.

Step 4: Activate the particle scouting strategy. With a certain probability, the particle scouting strategy is activated. Selected particles perform several guided jumps toward unexplored zones, improving the algorithm's ability to escape local optima.

Step 5: Check boundary conditions and correct positions. Each particle's position is validated against spatial constraints (e.g., boundaries, forbidden zones). Any infeasible solutions are repaired and projected back into the feasible space.

Step 6: Update personal and global best solutions. Each particle's personal best (*pbest*) and the global best (gbest, *E_v*) are updated based on the evaluation function.

Step 7: Track optimal solutions. The *E_v* from each iteration is stored in the list *Ev_list* for further trend analysis and visualization.

Step 8: Detect local optima and trigger mutation-elimination strategy. If *E_v* stagnates over several iterations, the mutation-elimination strategy resets low-quality particles via Gaussian perturbation to restore search vitality.

Step 9: Check termination and output final results. Upon reaching the maximum iteration count *T*, the algorithm outputs the final optimized layout; otherwise, it returns to Step 3.

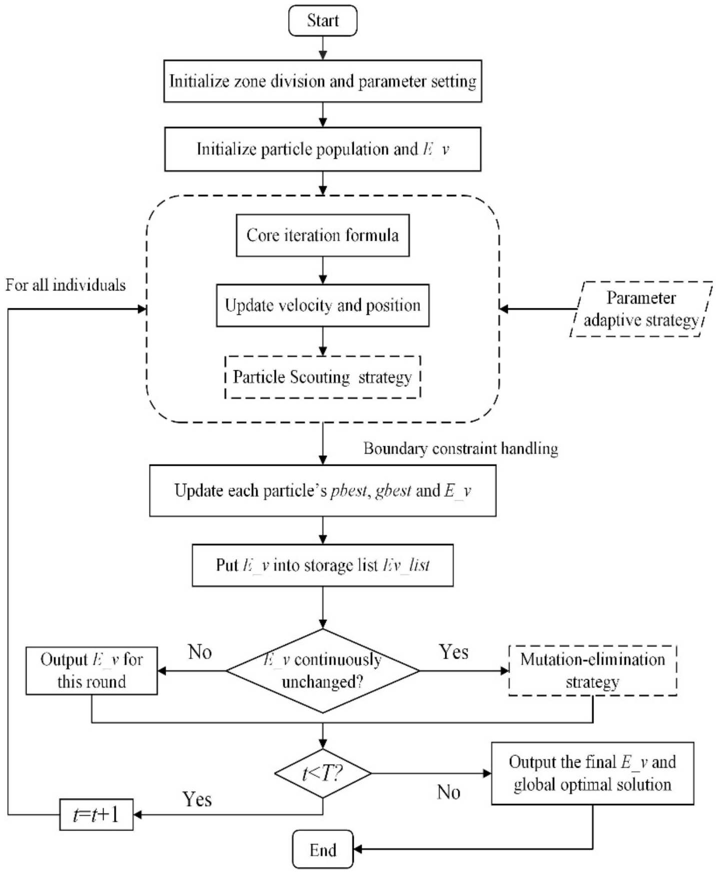



Fig. 4. Flowchart of equipment layout optimization method.

# 4. Experimental simulation and analysis

## 4.1 Case information and experimental settings

To verify the effectiveness of the proposed method, a real-world ship engine room layout case from [6] is used, focusing on first-level collaborative equipment. Experiments are conducted on a Windows 11 system using Python 3.12, executed on an AMD Ryzen 7 5800H with Radeon Graphics. As shown in Fig. 5, the parameterized model includes nine key devices (E1–E9). Based on expert knowledge, the engine room is divided into two main layout zones, with initial equipment positions set near zone centers. Fixed equipment E1 and E2 are preset at (33.5, 53, 16) and (15, 6, 30.5), respectively, and relevance coefficients are adopted from the original study. To evaluate performance, comparative tests are conducted against expert layouts and standard PSO, assessing accuracy, robustness, and practical applicability. For fairness, identical parameter settings are used for both PSO and AEPSO: $c_1 = c_2 = 1.5$, $w_{min} = 0.5$, $w_{max} = 0.9$, with 20 runs, 50 particles, and 500 iterations. Results are presented in Fig. 6, Fig. 7, and Table 1, where $E\_v$ denotes the layout evaluation score, ELEE represents expert benchmarks, and Best_c_iter indicates the best convergence iteration.

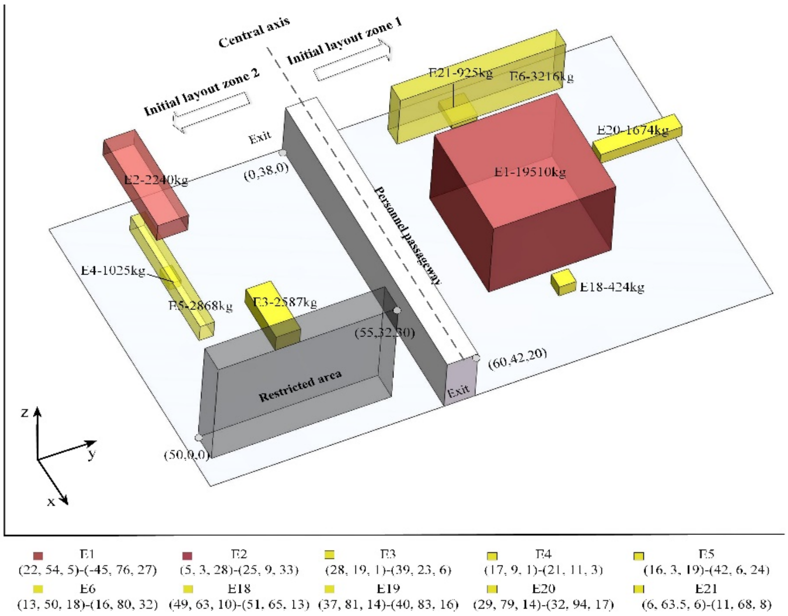



Fig. 5. Parametric illustration of the original engine room.

## 4.2 Analysis and discussion of test results

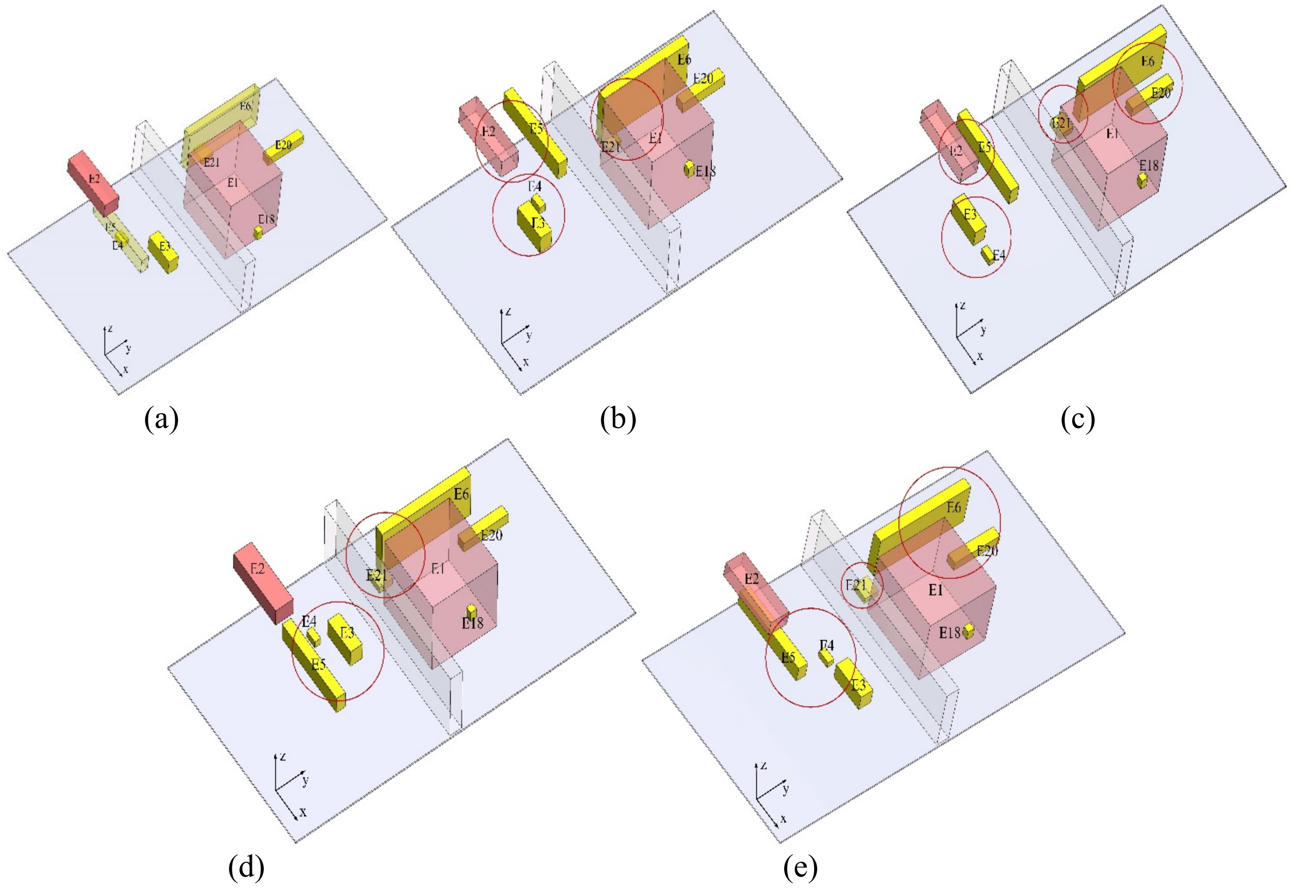
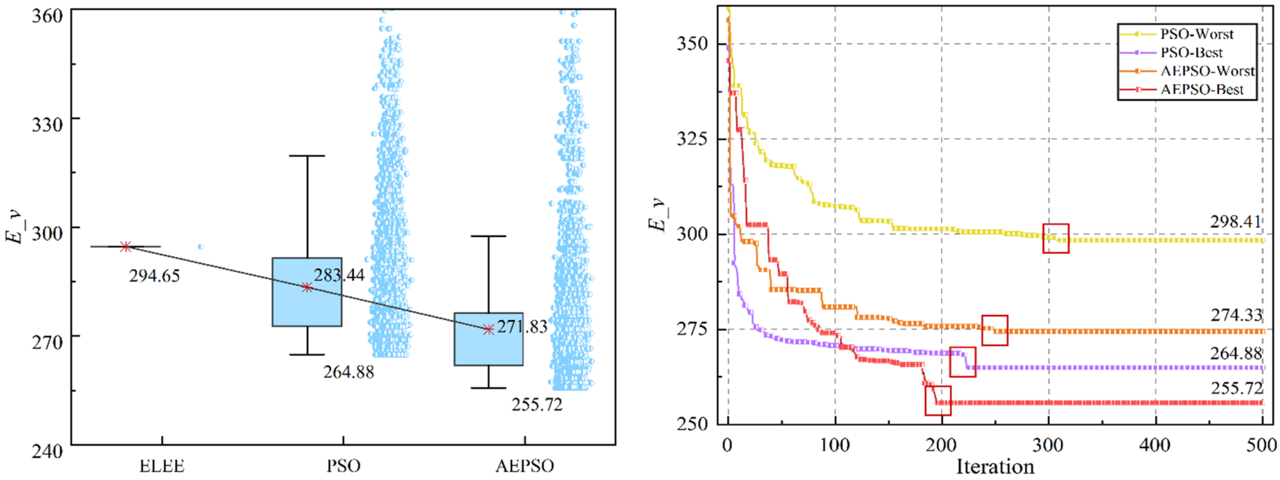



Fig. 6. Comparison of optimal layout schemes (a) ELEE; (b) PSO-Best; (c) PSO-Worst; (d) AEPSO-Best; (e) AEPSO-Worst.




(a) (b)

Fig. 7. Comparison of optimization performance data for various algorithms (a) All test results; (b) Optimal test results.

This study conducted comparative experiments among the ELEE, the standard PSO algorithm, and the proposed AEPSO algorithm. All methods share a common optimization logic focused on balance, relevance, and compliance. Through iterative computations, the best and worst layout schemes were obtained (as illustrated in Fig. 6, with major changes marked), along with detailed optimization performance metrics (Fig. 7 and Table 1). The following key conclusions can be drawn: (1) AEPSO outperforms the ELEE in terms of best evaluation results, demonstrating its practical capability in addressing complex layout requirements under practical engineering conditions; (2) Compared to standard PSO, AEPSO shows comprehensive superiority. The best evaluation value $E\_v$ achieved by AEPSO is 3.5% higher than that of PSO. The performance gap widens to 4.1% in terms of average evaluation value, indicating AEPSO's enhanced stability and consistency across multiple runs. In the worst-case results, the $E\_v$ gap between PSO and AEPSO reaches 8.1%, and even the worst performance of AEPSO still outperforms ELEE, highlighting the algorithm's robustness in maintaining layout quality under extreme conditions; (3) In terms of convergence characteristics, Fig. 7(b) clearly shows that AEPSO converges within the range of approximately 195 to 260 iterations, indicating a significantly faster optimization speed compared to standard PSO. Moreover, AEPSO leverages a flexible and fine-grained search mechanism to reduce parameter sensitivity and dynamically adjust search step size and ranges based on the layout environment. In summary, based on 20 independent test runs, AEPSO consistently delivers superior performance in both best and worst cases. It effectively identifies critical spatial conflicts in highly constrained and interdependent layout scenarios, demonstrating strong robustness, precision, and engineering applicability.

Table 1. Comprehensive comparison of evaluation data.

| | Best E_v | Deviation | Worst E_v | Deviation | Mean E_v | Deviation | Best_c_iter | Deviation |
|---|---|---|---|---|---|---|---|---|
| ELEE | 294.65 | 13.2% | 294.65 | 6.9% | None | None | None | None |
| PSO | 264.88 | 3.5% | 298.41 | 8.1% | 283.44 | 4.1% | 223 | 12.6% |
| AEPSO | 255.72 | None | 274.33 | None | 271.83 | None | 195 | None |

## 5. Conclusion

This study focuses on the complex optimization of equipment layout in ship engine rooms and proposes an intelligent design method that integrates an enhanced AEPSO algorithm with multiple adaptive strategies. The main conclusions are as follows:

(1) Parameter Adaptation: To address the rigidity of fixed PSO parameters, a dynamic adjustment mechanism for inertia weight and learning factors is introduced, enabling global exploration in early stages and refined local search later. This improves phase adaptability and overall optimization efficiency.

(2) Particle Scouting: To enhance search diversity and prevent premature convergence, an independent scouting mechanism is designed. Scout particles conduct localized perturbation-based exploration and return valuable information to the main population, facilitating collaborative multi-source optimization under complex constraints.

(3) Mutation-Elimination: A Gaussian mutation and adaptive elimination strategy is employed to inject diversity and discard low-quality particles. This maintains population vitality and enhances global search capability, particularly for highly coupled layout scenarios.

(4) SELD-Oriented Layout Framework: A complete intelligent layout method is developed based on SELD objectives and constraints. Multiple constraint checks ensure engineering feasibility, while trajectory tracking and stagnation detection trigger adaptive mutation. Experimental validation against expert designs and standard PSO confirms the method's effectiveness and applicability.

In conclusion, the proposed method addresses the limitations of conventional algorithms in adaptability, accuracy, and engineering relevance, offering a robust solution for high-dimensional, multi-objective, and strongly coupled layout problems. Future research will consider additional engineering factors such as structural integrity and installation processes to further refine evaluation metrics and enhance generalizability.

## References

[1] Jafaryeganeh, H., Ventura, M., Soares, C. G. Application of multi-criteria decision-making methods for selection of ship internal layout design from a Pareto optimal set. Ocean Eng. 2022, 202, 107151.

[2] Meng, X.; Sun, H.; Kang, J. Equipment Layout Optimization Based on Human Reliability Analysis of Cabin Environment. J. Mar. Sci. Eng. 2021, 9(11), 1263.

[3] Lee B C, Choi Y, Chung H. Firefighting equipment arrangement optimization for an offshore platform considering travel distances[J]. Journal of Marine Science and Engineering, 2021, 9(5): 503.

[4] Wang Y, Jiang Y, Gu Y. Intelligent 3D layout optimization design of ship engine room based on knowledge-based engineering. Ocean Engineering, 2024, 295, 116966.

[5] Li J, Liu T, Ling B, et al. Optimization of ship engine room equipment layout based on a two-stage multi-objective intelligent design method. Chinese Journal of Ship Research, 2024, 19(6): 150–160. [in Chinese].

[6] Zhang, H.; Yu, Y.; Zhang, Q.; Yang, Y.; Liu, H.; Lin, Y. A bidirectional collaborative method based on an improved artificial fish swarm algorithm for ship pipe and equipment layout design. Ocean Engineering, 2024, 296, 117045.

[7] Zhang H, Yu Y*, Song Z, Han Y, Yang Z, Ti L. Method for Collaborative Layout Optimization of Ship Equipment and Pipe Based on Improved Multi-Agent Reinforcement Learning and Artificial Fish Swarm Algorithm. Journal of Marine Science and Engineering, 2024, 12(7): 1187.

[8] Kennedy J, Eberhart R. Particle swarm optimization. Proceedings of ICNN'95-International Conference on Neural Networks. IEEE, 1995, 4: 1942-1948.

[9] Yoshida H, Kawata K, Fukuyama Y, et al. A Particle Swarm Optimization for Reactive Power and Voltage Control Considering Voltage Security Assessment. IEEE Trans on Power Systems, 2000, 15(4): 1232-1239

[10] Abido M A. Optimal Design of Power System Stabilizers Using Particle Swarm Optimization. IEEE Trans on Energy Conversion, 2002,17(3): 406-413

[11] Eberhart R C, Hu Xiaohui. Human Tremor Analysis Using Particle Swarm Optimization. Proc of the IEEE Congress on Evolutionary Computation. Washington, USA, 1999: 1927-1930.

[12] Ziyi S, Jing Z. Research on Prediction of Housing Prices Based on GA-PSO-BP Neural Network Model: Evidence from Chongqing, China. International Journal of Foundations of Computer Science, 2022, 33 (06n07)

[13] Tan W, Li X. Research on particle swarm optimization algorithm. Computer Technology and Development, 2009, 19(3): 87–90. [in Chinese]

[14] Du W, Li Y, Shi J, et al. Applying an improved particle swarm optimization algorithm to ship energy saving. Energy, 2023, 263: 126080

[15] Nazemian A, Ghadimi P. Shape optimisation of trimaran ship hull using CFD-based simulation and adjoint solver. Ships Offshore Struct, 2022,17(2):359-373.

[16] Zhang S, Zhang B, Tezdogan T, Xu L, Lai Y. Research on bulbous bow optimization based on the improved PSO algorithm. China Ocean Eng, 2017, 31(4):487-494.

[17] Wentie N, Haiteng S, Yaxiao N, et al. Ship Pipe Routing DesignUsing NSGA-II and Coevolutionary Algorithm. Mathematical Problems in Engineering, 2016, 2016:1-21.

[18] Zhang Q, Lin, Y. Integrating multi-agent reinforcement learning and 3D A* search for facility layout problem considering connector-assembly. Intell. Manuf. 2023, 1–26.