

Article

An Optimization Method for Ammunition Support Operation Scheduling and Personnel Allocation in the Shipborne Aircraft Intermediate Ordnance Staging Deck

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Abstract

The efficiency of ammunition support operations in the aircraft carrier intermediate ordnance staging deck is critical to sortie generation rates in naval aviation, yet joint scheduling and personnel allocation in this multistage, resource-constrained environment remains a challenging bi-objective optimization problem. This study develops a framework integrating an improved Nondominated Sorting Genetic Algorithm II (NSGA-II) with a marginal-benefit-based iterative feedback mechanism. The intermediate ordnance staging deck support process is decomposed into individual ammunition processing stations and formulated as a processflow model incorporating operation sequencing and personnel specialization constraints. A constraint decision model then dynamically reconciles the minimization of total makespan and personnel workload equilibrium through iterative marginal-benefit comparison across support teams. The NSGA-II is enhanced with an adaptive crossover-mutation mechanism and an improved elitism preservation strategy to strengthen global search capability. Validation on a typical carrier intermediate ordnance staging deck scenario demonstrates that the improved NSGA-II outperforms the conventional NSGA-II in convergence speed and Pareto front quality. Under the optimized configuration, the total makespan remains 3600 s with a workload balance metric of 1075 even as ammunition quantity doubles from two to four units. The proposed framework offers practical decision support for carrier ammunition operations and extends to other resource-constrained multi-objective scheduling domains.

Keywords: carrier-based aircraft; ammunition support; intermediate ordnance staging deck operations; personnel allocation; multi-objective optimization; NSGA-II

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1. Introduction

1.1. Background

In modern naval warfare, aircraft carriers must maintain continuous combat readiness to respond to the rapidly changing operational requirements. The sortie generation

capability of carrier-based aircraft is therefore a core determinant of aircraft carrier combat effectiveness. Before an aircraft can be launched, a series of tightly coupled support operations must be completed on and below the flight deck, including inspection, fueling, ammunition preparation, weapon loading, and dispatch coordination. Different from land-based aircraft servicing, shipboard ordnance preparation is restricted by narrow deck space, rigid task sequences and shared human-equipment resources, all of which jointly restrict feasible scheduling schemes [1–4]. Any delay in ammunition preparation or transfer may propagate to the flight deck schedule and reduce the sortie rate of the carrier air wing.

Ammunition support is one of the most time-consuming and labor-intensive activities in the carrier-based aircraft support process. Before flight deck weapon loading can commence, mission-required munitions must be retrieved from the magazine area, transferred through internal elevators, temporarily staged, assembled, inspected, and then delivered upward to the deck ammunition well. This intermediate operation area is referred to in this study as the intermediate ordnance staging deck. Serving as the critical interface between the lower magazine layer and the upper flight deck layer, the intermediate ordnance staging deck is responsible for receiving ammunition from lower elevators, conducting inspection and assembly operations, allocating temporary holding resources, and dispatching finished ammunition batches to the upper elevator according to the mission plan.

The intermediate ordnance staging deck is a resource coordination hub in which multiple specialized support groups, transfer devices, elevators, operation stations, and ammunition batches interact under spatial and temporal constraints. Its scheduling problem has three prominent characteristics. First, the available space for personnel and equipment is limited. Simply increasing the number of workers or support devices may increase congestion and coordination conflicts rather than reduce completion time [5,6]. Second, the intermediate ordnance staging deck operation contains several sequential and partially parallel procedures, such as elevator-out transport, inspection, assembly, elevator-in transport, and handover to the upper layer. These procedures have strict precedence relationships and may require different personnel qualifications. Third, the operational objective is inherently multi-objective: commanders expect the ammunition batch to be completed as early as possible, while managers must also avoid unreasonable personnel workload imbalance, excessive fatigue, and inefficient staffing.

From an optimization perspective, intermediate ordnance staging deck ammunition support can be abstracted as a multi-resource, multi-constraint, multi-objective scheduling problem. Ammunition rounds or batches can be regarded as jobs; operation procedures correspond to ordered processing steps; and qualified personnel groups act as flexible processing resources. This structure is closely related to the flexible job shop scheduling problem (FJSP), which has been widely used to model systems in which each operation can be assigned to one of several eligible resources [7–10]. However, intermediate ordnance staging deck ammunition support differs from conventional workshop scheduling because personnel allocation and operation scheduling are strongly coupled. A staffing plan determines the feasible schedule space, but the value of a staffing plan can only be evaluated through the resulting schedule. Therefore, a sequential approach that first fixes personnel allocation and then optimizes the schedule may fail to identify an effective trade-off between operation time and personnel utilization.

To address this issue, this paper studies the ammunition support operation scheduling problem at the carrier-based aircraft intermediate ordnance staging deck. A bi-objective scheduling model is formulated to simultaneously minimize the batch completion time and the imbalance of personnel workload. An improved Non-dominated Sorting Genetic Algorithm II (NSGA-II) is then developed as the core optimization algorithm, and a constraint decision model is introduced to coordinate the relationship between personnel

configuration and schedule quality. The aim is to generate a practical intermediate ordnance staging deck ammunition support scheme that satisfies operational precedence constraints, personnel constraints, and mission timing requirements while maintaining a reasonable workload distribution.

1.2. Literature Review

The present study is closely related to three streams of research: carrier-based aircraft support scheduling, flexible job shop and resource-constrained scheduling, and personnel allocation with workload balancing.

Research on carrier-based aircraft support scheduling has mainly focused on flight deck operations, where multiple aircraft, personnel teams, support equipment, and fixed service stations must be coordinated in a narrow and dynamic environment. Existing studies commonly model flight deck support as a resource-constrained project scheduling problem or its extensions. Cui et al. [1] established an integrated optimization model for flight deck operation scheduling and resource configuration, considering resource transfer time and multiple execution modes, and solved the resulting multi-objective problem using a hyper-heuristic framework. Cui et al. [2] further proposed a dual-population multi-operator genetic algorithm for multi-aircraft flight deck scheduling with resource transfer times. Su et al. [3] examined a resource-constrained multi-aircraft scheduling problem in which both aircraft transfer and resource transfer are considered, showing that ignoring aircraft movement may lead to unrealistic schedules. Other studies have addressed robust scheduling under uncertain activity durations [4], deck path planning and dispatch control [11], fixed aviation support station configuration [12], and automated or learning-based scheduling for carrier flight deck operations [13,14]. These studies demonstrate that carrier aviation support is essentially a constrained and dynamic scheduling system.

Nevertheless, most publicly available carrier scheduling studies concentrate on the flight deck. The ammunition support chain below the deck, especially the intermediate ordnance staging deck between magazines and the flight deck, has received much less attention. Existing ammunition support studies often treat storage retrieval, vertical transfer, deck transportation, and loading as a unified full-process problem. Such integrated modeling is useful for global analysis, but it tends to hide the independent operational characteristics of each layer. In practice, the magazine layer, intermediate ordnance staging deck, and deck layer have different resource structures, working spaces, and disturbance patterns. A full-process model may therefore be too coarse to capture the intermediate ordnance staging deck's internal bottlenecks, especially the trade-off between adding personnel and avoiding congestion. Recent formal modeling work on carrier-borne aircraft ammunition support also indicates that ammunition support scheduling requires rigorous representation of resource relationships and operation logic [15]. This motivates a layer-specific study of intermediate ordnance staging deck ammunition support operations.

Flexible job shop scheduling provides an important theoretical basis for the abstraction used in this paper. The FJSP extends the classical job shop scheduling problem by allowing each operation to be processed by one of several eligible machines or resources, thereby better representing flexible and decentralized production environments [7–10]. Because FJSP and its multi-objective variants are NP-hard, exact methods are often computationally expensive for medium and large-scale cases. Metaheuristic and evolutionary algorithms have therefore become dominant solution approaches. Deb et al. [16] proposed NSGA-II, which remains one of the most widely used multi-objective evolutionary algorithms due to its fast non-dominated sorting and crowding-distance-based diversity preservation. Zhang and Li [17] proposed MOEA/D, offering a decomposition-based alternative for multi-objective optimization. Recent surveys and studies show that genetic

algorithms, particle swarm optimization, Jaya algorithms, swarm intelligence methods, and hybrid evolutionary algorithms continue to play major roles in FJSP research [18–22]. As a classic multi-objective optimization method, NSGA-II has also been widely applied to resource scheduling and workload balancing problems in complex industrial scenarios [23].

In recent years, FJSP research has moved toward more realistic resource coupling and dynamic decision-making. For example, studies have incorporated transport constraints, controllable processing times, energy consumption, machine breakdowns, and dynamic job arrivals [24–28]. Deep reinforcement learning and graph neural networks have also been introduced to improve the real-time response capability of scheduling systems. Song et al. [29] proposed a graph neural network and deep reinforcement learning method for flexible job-shop scheduling, while Su et al. [30] developed a preference-conditioned graph reinforcement learning approach for fast Pareto set approximation in multi-objective FJSP. Wu et al. [31] studied dynamic FJSP in Processes using a deep reinforcement learning approach, and Lei et al. [32] developed a hierarchical reinforcement learning framework for large-scale dynamic FJSP with random job arrivals. These works indicate a clear trend: scheduling models are increasingly expected to reflect realistic resource constraints and to provide actionable decisions under complex operating environments.

The various intelligent optimization algorithms discussed above exhibit distinct applicability characteristics and inherent limitations. For instance, while particle swarm optimization (PSO) [33] features straightforward parameter configuration and rapid convergence, it is prone to becoming trapped in local optima when applied to high-dimensional discrete combinatorial optimization problems. Moreover, its single-best-solution guidance mechanism renders it difficult to obtain a well-distributed Pareto front in a single run. Ant colony optimization (ACO), by virtue of its positive-feedback pheromone mechanism, excels in path-construction problems; however, its convergence behavior is highly sensitive to the selection of initial parameters, and it is susceptible to stagnation. Furthermore, ACO [34] was originally designed for single-objective optimization, and extending it to multi-objective problems necessitates the additional incorporation of non-dominated sorting and diversity maintenance strategies, which substantially increases algorithmic complexity. Reinforcement learning (RL) [35] has demonstrated strong self-learning and adaptive potential in dynamic sequential decision-making scenarios. Nevertheless, its effective training relies on a large number of interaction samples and a carefully designed reward function. In static deterministic scheduling problems, RL does not yet exhibit a clear advantage over evolutionary algorithms in terms of solution efficiency and convergence stability, and it struggles to directly handle explicit hard constraints inherent in such problems. In contrast, genetic algorithms, as population-based evolutionary search methods, possess inherent parallelism and global search capability. They do not require gradient information of the problem and exhibit favorable structural compatibility with discrete combinatorial optimization problems. Among them, the non-dominated sorting genetic algorithm NSGA-II [36], through its mechanisms of fast non-dominated sorting, crowding distance computation, and elitist preservation, is capable of generating a uniformly distributed set of Pareto-optimal solutions in a single run. It has thus become one of the most mature and widely adopted algorithmic frameworks in the field of multi-objective scheduling. Considering NSGA-II's established application track record in multi-objective scheduling contexts, its natural suitability for encoding discrete decision variables, and the practical advantage of providing multiple non-dominated alternatives for decision-makers to evaluate trade-offs in a single run, this paper adopts an improved NSGA-II algorithm to solve the problem under investigation.

Personnel allocation and workload balancing form another important research stream. In many labor-intensive systems, personnel are not identical resources; they differ in skill, qualification, fatigue, and workload tolerance. Recent production scheduling

studies therefore increasingly include worker assignment, ergonomic constraints, and workload equity. Usman and Lu [37] studied job-shop scheduling with limited flexible workers and ergonomic factors, jointly minimizing makespan, maximum worker workload, and human energy expenditure. Other work has integrated machine layout, transporter allocation, and worker assignment into job-shop scheduling, showing that worker assignment with skill differences can reduce workload imbalance and improve system performance [38]. Human factors, including worker flexibility and learning–forgetting effects, have also been incorporated into multi-objective FJSP models [39]. In addition, resource-constrained project scheduling studies emphasize that resource leveling and workload balance are essential when activity durations are uncertain or shared resources are scarce [19,40]. For intermediate ordnance staging deck ammunition support, these considerations are especially important because fatigue, improper staffing, or uneven workload may directly affect operation reliability and safety.

Existing research has laid a solid theoretical foundation for modeling the scheduling of ammunition support resources on aircraft carriers; however, there still exist research gaps [22,40]:

1. Current studies on carrier-based aircraft ammunition scheduling mainly focus on the flight deck level, whereas the transfer level between the magazine and the flight deck has rarely been investigated. As a critical link bridging the magazine and deck ammunition support, the transfer level encompasses several support processes that must be executed, such as transfer, electromechanical operations, recording, and assembly. This level exhibits strong operational independence and considerable room for scheduling optimization. Most existing studies tend to adopt whole-process modeling, which cannot accurately reflect the internal scheduling efficiency of the transfer level.
2. Traditional Flexible Job-shop Scheduling Problem (FJSP) models usually treat equipment as stable processing resources, with common optimization objectives including maximizing equipment utilization, minimizing energy consumption, and minimizing completion time. However, since an aircraft carrier is a vital national defense asset, its resource allocation is often very abundant, making some of these objectives not the primary concerns. Operations at the transfer level are mainly performed by personnel teams; therefore, crew numbers, workload, and qualifications must be co-optimized with the support completion time to achieve a balanced personnel allocation. These aspects have rarely been addressed in existing studies.
3. Under a highly constrained search space, the standard NSGA-II algorithm easily loses population diversity, which may lead to premature convergence and difficulty in thoroughly exploring the trade-off relationship between personnel allocation and support completion time. Existing improvement methods proposed by other scholars may not be suitable for the scheduling requirements of the carrier transfer level, creating an urgent need to develop a superior solution algorithm.

To fill these research gaps, the innovations of this study are primarily reflected in the following:

4. The ammunition support process at the transfer level is analyzed as an independent operational scenario situated between the magazine level and the flight deck level. Its operational procedures, resource constraints, and scheduling requirements are formalized, providing a theoretical basis for future scholars studying related scenarios.
5. By mapping ammunition support operations onto an FJSP-like structure, a bi-objective scheduling optimization model that considers differences in personnel workload is constructed for the carrier transfer level. This refines the modeling of the carrier

ammunition support process down to the transfer level, thereby expanding the scope for ammunition support optimization.

6. A solution framework combining an improved NSGA-II with an iterative feedback mechanism based on marginal benefit is developed, rather than merely employing a simple genetic algorithm. While enhancing solution diversity and convergence performance, this framework also coordinates personnel allocation and job scheduling, enabling the method to identify balanced support schemes rather than optimizing personnel allocation or time scheduling in isolation.

The remainder of this paper is organized as follows. Section 2 analyzes the intermediate ordnance staging deck ammunition support operation process and defines the scheduling problem. Section 3 constructs the mathematical model and objective functions. Section 4 presents the improved NSGA-II algorithm and the constraint decision model. Section 5 reports the simulation experiments and comparative analysis. Section 6 concludes the study and discusses future research directions.

2. Intermediate Ordnance Staging Deck Ammunition Support Operation Process and Problem Definition

The rapid sortie generation capability of carrier-based aircraft is a decisive factor in modern naval warfare, and the efficiency of ammunition support operations directly governs combat response speed. Within the carrier ammunition support workflow, the intermediate ordnance staging deck, as the intermediate link between the lower magazine and the flight deck, performs the core tasks of ammunition receiving, assembly, and transfer. Intermediate ordnance staging deck operations face the following salient challenges:

7. Resource constraints versus efficiency: The intermediate ordnance staging deck has severely limited space. Indiscriminately adding personnel or equipment may cause operational congestion, yet insufficient resources prolong ammunition support time and disrupt flight deck scheduling. Balancing personnel allocation with operational efficiency under tight spatial constraints is an urgent optimization problem.
8. Multi-objective conflict: It is necessary to simultaneously minimize the ammunition support completion time (to maintain an adequate flight deck time buffer) and balance personnel workload (to avoid excessive fatigue or resource waste). These two objectives are inherently in tension, and traditional scheduling methods cannot readily reconcile them.
9. Complex procedural constraints: Ammunition support spans multiple stages—elevator-out transport, assembly, and elevator-in transport—each requiring coordination among different specialized support groups (e.g., transport group, electromechanical group) under strict precedence dependencies, further compounding scheduling complexity.

This paper takes intermediate ordnance staging deck ammunition support operations as the research object and abstracts them as a multi-constraint, multi-objective NP-hard scheduling problem. The goal is to optimize personnel allocation and operation scheduling through an improved NSGA-II algorithm and a constraint decision model, achieving the dual objectives of minimizing operation time and balancing personnel workload, thereby providing theoretical support for combat-oriented carrier operations.

2.1. Analysis of Intermediate Ordnance Staging Deck Ammunition Support Operations

Taking the internal structure of an American-style aircraft carrier as a reference, the carrier intermediate ordnance staging deck is typically situated in the mid-forward section of the “02” deck and is primarily responsible for material transfer and resource allo-

cation. As a critical component of carrier-based aircraft support, ammunition must be assembled at the intermediate ordnance staging deck before being transported via the upper-deck elevator to the flight deck for subsequent procedures. Compared with flight deck operations, the intermediate ordnance staging deck ammunition support process is characterized by confined working spaces and fixed workflows. Although the specific equipment employed varies with ammunition type, the operational stages remain broadly consistent. After being lifted to the intermediate ordnance staging deck via the lower elevator, ammunition proceeds through two transport stages and one assembly stage, together with ancillary activities such as ammunition inspection and retrieval. Based on the intermediate ordnance staging deck ammunition support workflow, the three stages are detailed as follows.

Stage 1: Elevator-out Transport: Once the lower elevator lifts the ammunition to the intermediate ordnance staging deck, support personnel receive and inspect it, verifying type, quantity, and condition against combat mission requirements and recording the relevant data. Depending on ammunition type and operational needs, specialized equipment is then used to load the ammunition onto transfer vehicles. Loading procedures strictly follow anti-vibration and securing protocols to ensure in-transit stability. The loaded ammunition is transported to the assembly area via transfer vehicles, with support personnel monitoring vehicle status in real time to ensure safe transport and prevent collisions or tipping.

Stage 2: Ammunition Assembly: Upon arrival at the assembly area, ammunition enters the assembly stage—the most critical phase of the entire process, involving multiple steps. Prior to assembly, support personnel perform a detailed inspection to confirm the ammunition is free of damage and contamination and meets all safety standards. The inspection covers visual examination, integrity verification, and the elimination of any potential hazards. The assembly team prepares the required tools and equipment, conducting pre-operation checks to ensure all items are in proper working order. Key assembly tasks—such as guidance device installation and stabilizer fin attachment—are then performed according to the specific ammunition type, following strict technical specifications to guarantee stability and safety during use. The assembly process demands a high level of technical skill; certain critical steps must be executed by experienced senior technicians. Once assembly is complete, support personnel conduct a further inspection to verify that all components are correctly and securely fitted. Finally, the ammunition is marked with its type, assembly date, and operator identification for subsequent tracking and management.

Stage 3: Elevator-in Transport: The assembled ammunition must be transported to the flight deck through the elevator-in transport stage. The ammunition is reloaded onto transport vehicles, securely fastened to prevent any movement or tipping during transit. A final safety inspection of both ammunition and transport equipment is performed to confirm satisfactory condition. After loading, the ammunition is conveyed via transfer vehicles to the upper-deck elevator, where it queues for lifting to the flight deck. Support personnel coordinate with elevator operators to ensure safe placement of the ammunition inside the elevator and maintain communication with the upper-deck operations team throughout the process to achieve a seamless handover.

The entire intermediate ordnance staging deck ammunition support process adheres strictly to fixed procedures. Operation tasks within each stage are identified by procedure codes indicating the operation sequence. The duration of each support procedure varies by ammunition type. For analytical convenience, this paper assumes identical operation times and procedures for air-to-air missiles (AAM), air-to-ground missiles (AGM), and air-to-ship missiles (ASM). The support process flow chart is presented in Figure 1.

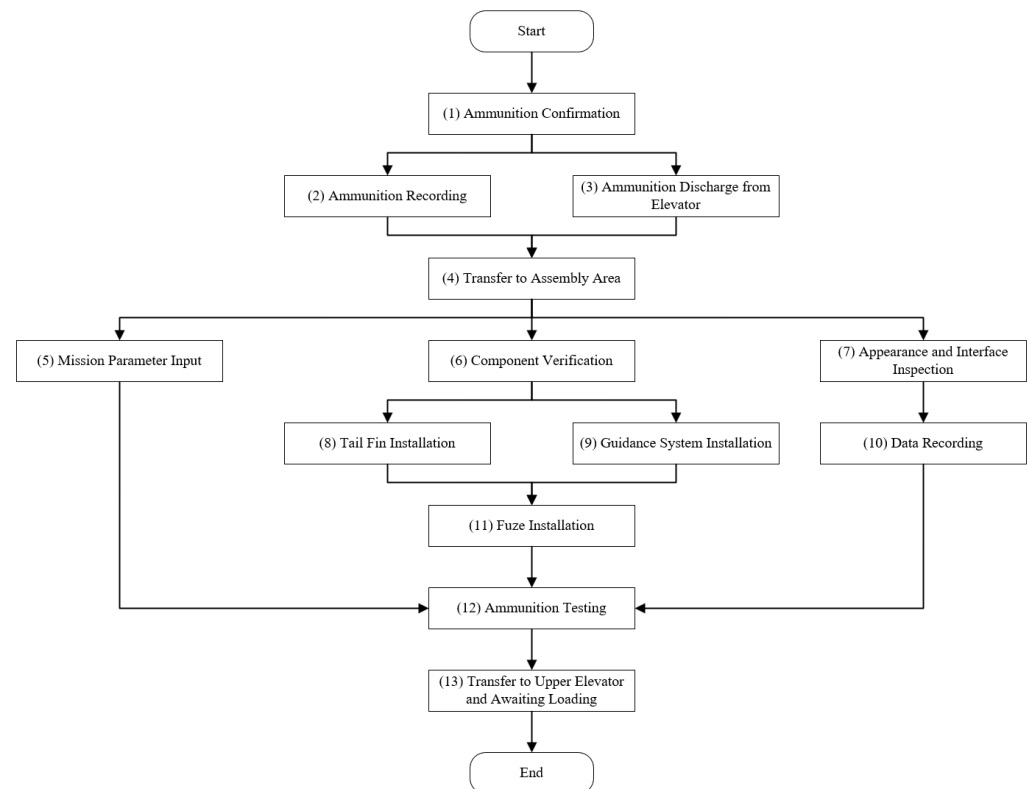


Figure 1. Ammunition support operation flow chart of the intermediate ordnance staging deck.

2.2. Problem Definition

This paper models the intermediate ordnance staging deck ammunition support operation as analogous to the work-piece processing problem in a production workshop. The objective is to determine the optimal staffing level for each ammunition support group and the optimal assembly and transfer schedule under balanced personnel workload, thereby minimizing the maximum ammunition support operation completion time while satisfying all constraints.

The relevant notation and definitions are provided in Table 1.

Table 1. Description of relevant definitions.

Symbol	Definition
$DY = \{1, 2, 3, i, \dots, I\}$	Set of ammunition items supported at the intermediate ordnance staging deck
$BR = \{1, 2, \dots, b, \dots, B\}$	Set of support personnel at the intermediate ordnance staging deck
$JD = \{1, 2, \dots, j, \dots, J\}$	Set of standard ammunition support operations in the discretized time-node set
$TJ = \{1, 2, \dots, t, \dots, T^*\}$	Set of standard operation times for transfer-layer ammunition support procedures
$TB = \{t_1, t_2, \dots, t_j, \dots, t_j\}$	Set of standard operation times for transfer-layer ammunition support procedures
O_{ij}	The j th support operation of the i th ammunition item
T_i^S	Start time when the i th ammunition item arrives at the intermediate ordnance staging deck for support operations
T_{ij}^S	Start time of the j th support operation for the i th ammunition item

T_{ij}^E	End time of the j th support operation for the i th ammunition item
Q_{ij}	Set of immediate predecessor operations of the j th support operation for the i th ammunition item in the intermediate ordnance staging deck
T_i^F	Completion time of the last support operation for the i th ammunition item in the intermediate ordnance staging deck
T	Completion time of ammunition support operations for the current task batch in the intermediate ordnance staging deck
G	Average workload balance degree of all support personnel in the intermediate ordnance staging deck
$\Omega = \{1, 2, 3, 4\}$	Four types of support groups: transfer, electromechanical, recording, and assembly
$SW = \{1, 2, 3, \dots, n, \dots, N_\omega\}$	Set of personnel in the ω th type of support group
N_ω	Number of personnel in the ω th type of support group
$N_{ij\omega}$	Number of personnel from the ω th type of support group required for support operation O_{ij} in the intermediate ordnance staging deck
X_{ijbt}	Decision variable indicating whether support personnel b performs operation O_{ij} at time t
Y_{ijb}	Decision variable indicating whether support personnel br is assigned to operation O_{ij}
$Z_{ij\omega n}$	Decision variable indicating whether the n th support personnel in the ω th type of support group is assigned to operation O_{ij}

3. Model Construction

3.1. Objective Functions

To improve both the efficiency and the rationality of intermediate ordnance staging deck ammunition support operations, two optimization objectives are established targeting the key operational concerns: minimizing the intermediate ordnance staging deck ammunition support completion time and minimizing the imbalance in support personnel workload. As the intermediate link connecting the magazine deck and the flight deck, the intermediate ordnance staging deck's efficiency directly shapes the overall support schedule. To ensure an adequate time buffer for the flight deck, the intermediate ordnance staging deck operation time must be minimized. Simultaneously, support personnel are the primary agents executing transfer operations; rational task allocation not only enhances operational efficiency but also prevents fatigue and errors arising from excessive individual workloads. Personnel workload balance is therefore an essential optimization consideration. Together, these two objectives reflect both a drive for efficiency and a commitment to sound personnel management, providing clear direction for the optimization model. The specific objective functions are formulated as follows.

10. Minimize the completion time of intermediate ordnance staging deck ammunition support.

Ammunition support operations are subject to stringent time-window constraints. The ammunition support time should be minimized under all applicable constraints to maximize the time buffer available for flight deck ammunition scheduling. The objective function for minimizing the intermediate ordnance staging deck ammunition support completion time can be expressed as:

$$f_1 = \min T_{\max}$$

$$T_{\max} = \max T_i^F, \forall i \in DY \quad (1)$$

where $T_{\max}$ denotes the completion time of the latest support operation procedure for the i -th ammunition round in the mission batch.

11. Minimize the imbalance in support personnel workload

Intermediate ordnance staging deck ammunition support operations are primarily executed by personnel operating specialized equipment. A reasonably balanced task allocation is essential for efficient and sustained operations. Achieving balanced working hours across support personnel not only improves overall operational efficiency but also reduces individual fatigue and prevents the errors and efficiency losses caused by excessive burden. Balanced allocation allows the full potential of all personnel to be realized, thereby enhancing overall team coordination and resilience to emergent events. Accordingly, this paper adopts the variance of support personnel operation time, as one of the optimization objectives—a smaller value indicates more rational task allocation and more equitable personnel utilization. Since the work intensity of individual procedures differs, evaluating workload balance purely on the basis of total operation time across all personnel would be misleading. Calculations are therefore performed separately for each support group. The specific computational method is as follows:

$$f_2 = \min G = \min \sum_{\omega \in \Omega} \sqrt{\frac{\sum_{b=1}^{N_{\omega}} (gT_{\omega b} - \overline{gT_{\omega}})^2}{N_{\omega}}} \quad (2)$$

where $gT_{\omega br}$ denotes the operation time of support personnel b in support group ω , and $\overline{gT_{\omega}}$ denotes the mean workload of support group ω , computed as:

$$gT_{\omega b} = \sum_{i=1}^I \sum_{j=1}^J Y_{ijb} \times t_j, \quad \forall b \in SW \quad (3)$$

$$\overline{gT_{\omega}} = \frac{\sum_{b \in S_{\omega}} gT_{\omega b}}{N_{\omega}} \quad (4)$$

3.2. Constraints

The following assumptions underpin the construction of the intermediate ordnance staging deck ammunition support personnel allocation and scheduling model:

12. Before support operations begin, the following conditions are met: the required number of support personnel is available; ammunition from the lower magazine has been dispatched to the intermediate ordnance staging deck; personnel are in position at the work area; and all equipment is fully tested and ready for immediate operation.
13. During support operations, uncertain or emergent events—such as mid-operation personnel substitutions or pauses, equipment failures, human errors, or accidents—and any other factors that could disrupt execution are not considered.
14. At any given moment, each support staff member can execute only one operation procedure, thereby avoiding operation conflicts.
15. The support operation procedures for all ammunition rounds to be serviced are identical.
16. The mission-required ammunition rounds are mutually independent, and their support operations do not interfere with one another.
17. Small-scale movement time of ammunition within the assembly area during the assembly process is disregarded.
18. Personnel workload depends solely on operation time and is independent of other factors.
19. Each procedure assigns specific support technical personnel; different support groups are responsible for different support procedures.

20. The time specified for each procedure already accounts for waiting and buffering periods and represents the standard operation working hours. Personnel are therefore not required to prepare in advance, avoiding unproductive idle time.

Based on the characteristics of the ammunition support process and the definition of the objective functions, the mathematical model for intermediate ordnance staging deck ammunition support personnel allocation and scheduling proposed in this paper includes the following principal constraints:

$$T_i^S \leq T_{ij}^S, \forall i \in DY; \forall j \in JD \quad (5)$$

Equation (5) ensures that ammunition support operations commence only after the required ammunition has arrived at the intermediate ordnance staging deck.

$$T_{ij}^E = T_{ij}^S + t_j, \forall i \in DY; \forall j \in JD \quad (6)$$

Equation (6) expresses the mathematical relationship among the start, execution, and completion times of ammunition support operation procedures, accounting for the influence of ammunition type.

$$\max(T_{i\eta}^E) \leq T_{ij}^S, \forall \eta \in Q_{ij} \quad (7)$$

Equation (7) enforces strict precedence constraints: a subsequent procedure may begin only after all of its immediate predecessor procedures have been completed.

$$\sum_{i=1}^I \sum_{j=1}^J X_{ijbt} \leq 1, \forall b \in BR; \forall t \in TJ \quad (8)$$

Equation (8) stipulates that, at any moment, each support staff member can execute at most one operation procedure for one ammunition round.

$$\sum_{n=1}^{N_\omega} Z_{ij\omega n} = N_{ij\omega}, \forall j \in JD; \forall \omega \in \Omega \quad (9)$$

Equation (9) ensures that the number of personnel assigned to an ammunition support operation matches the required count, and that the assigned personnel belong to the same support group.

$$X_{ijbt} \in \{0,1\}, Y_{ijb} \in \{0,1\}, Z_{ij\omega n} \in \{0,1\} \quad (10)$$

Equation (10) defines the Boolean domain of the decision variables.

4. Algorithm Design

This paper adopts the NSGA-II algorithm for solution generation and specifically improves the elitist preservation strategy to enhance the diversity of the iterative population. Finally, a constrained decision-making model is used to determine the personnel allocation of each support team and the scheduling of support operation procedures, so as to meet diversified ammunition support requirements while simultaneously optimizing objectives such as minimizing operation time and balancing personnel workload. The optimal scheduling scheme for the ammunition required by each task batch is then output.

4.1. Chromosome Encoding and Decoding

Considering that the personnel allocation and scheduling model needs to simultaneously address personnel quantity allocation and personnel selection, traditional operation-list encoding can represent operation sequences but has difficulty expressing the constraint relationships between personnel and operations. Moreover, illegal solutions are likely to be generated after crossover and mutation. Therefore, this paper adopts a matrix-based encoding method.

Let the number of supported ammunition items be I . Although the support time for each ammunition item may differ slightly, the operational process is identical. Each ammunition support operation consists of J operation procedures, and each procedure has restrictions on the type and number of required personnel. Accordingly, the chromosome matrix is defined as shown in Equation (11):

$$Z_{I,J} = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1J} \\ z_{21} & z_{22} & \cdots & z_{2J} \\ \vdots & \vdots & \ddots & \vdots \\ z_{I1} & z_{I2} & \cdots & z_{IJ} \end{bmatrix} \quad (11)$$

In Equation (11), each gene represents the set of support personnel IDs assigned to the j th operation procedure of the i th ammunition item. Since different procedures have explicit requirements regarding the professional category and number of support personnel, the value range of each corresponding gene must be restricted to the ID range of members in the relevant professional support group. The multidimensional matrix is expanded into a one-dimensional chromosome string with a length of I times J , so that each chromosome position corresponds one-to-one with an ammunition operation procedure. This encoding method makes the chromosome length dependent only on the number of ammunition items and the number of operation procedures. When the number of personnel changes, only the gene value range needs to be adjusted, thereby reducing encoding redundancy and effectively avoiding the generation of illegal chromosomes during crossover and mutation. Figure 2 shows an example of how the first ammunition item chromosome is encoded.

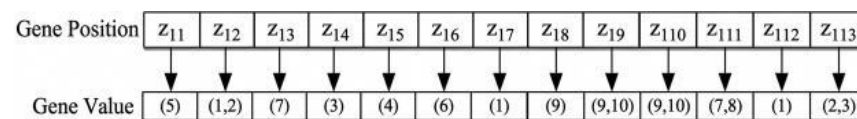


Figure 2. Example of chromosome encoding for the first ammunition item.

Before decoding, operation priorities need to be determined. In this paper, the arrival time of ammunition at the transfer deck is used as the initial priority, following the first-come, first-served principle. For the same ammunition item, if the procedures follow a serial logic, they are executed strictly according to precedence constraints. If a procedure is located in a parallel chain, the number of subsequent operations, the number of required support personnel, and the number of assigned operations of the relevant personnel are compared sequentially; the larger the value, the higher the priority. For different ammunition items, in addition to arrival time, ammunition with more subsequent operation procedures has higher scheduling complexity and should therefore be assigned a higher operation priority.

The decoding process draws on the idea of discrete events and adopts an event-driven mechanism. Three sets are defined: the unfinished operation set, the ongoing operation set, and the completed operation set. The specific steps are as follows. First, the personnel-operation assignment set is extracted from the chromosome, and the operations are sorted according to the priority rules. Second, it is determined in sequence whether the current procedure satisfies the precedence constraints and personnel requirement constraints. Once the conditions are satisfied, the start time and completion time of the procedure are recorded, and the operation sets are updated. Finally, after all operation procedures have been completed, the completion time of ammunition support for the task batch and the personnel workload balance value are calculated as the objective function values of the individual.

4.2. Improved Elitist Preservation Strategy

After non-dominated sorting and crowding distance calculation, NSGA-II employs an elitist preservation strategy to transfer elite individuals to the next generation, thereby accelerating population evolution and improving the quality of the Pareto front. However, the conventional strategy may result in insufficient population diversity, thereby limiting the global search capability of the algorithm and increasing the risk of being trapped in local optima. To address this issue, this study improves the elitist preservation strategy of NSGA-II and proposes a hierarchical graded preservation strategy, as illustrated in Figure 3.

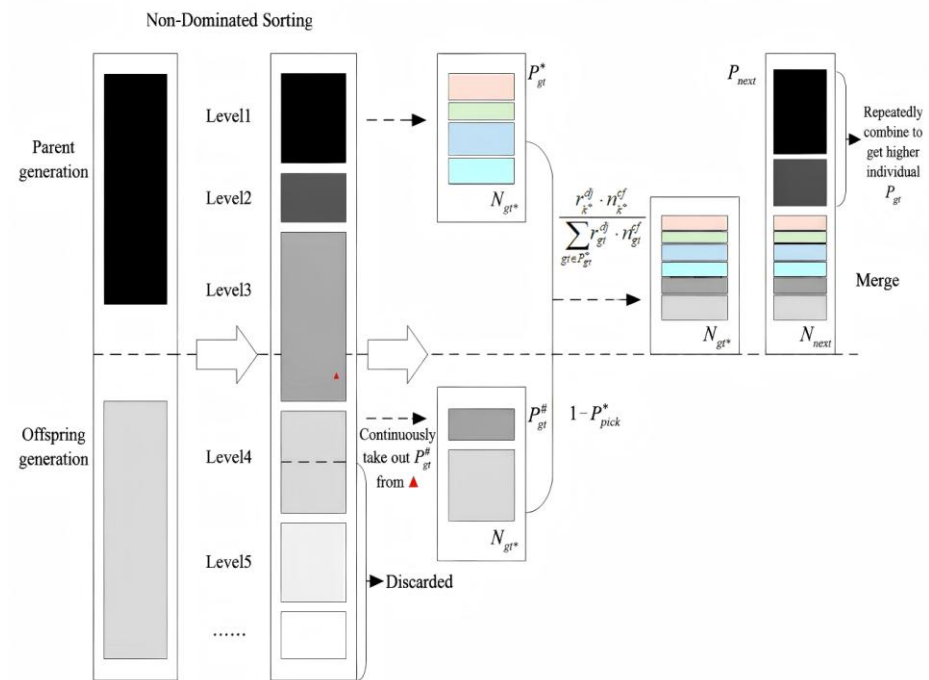


Figure 3. Schematic diagram of the hierarchical graded preservation strategy.

As seen in Figure 3, the detailed procedure is as follows:

Step 1: Traverse all non-dominated solution sets, record the non-dominance rank r_{gt} and repetition count n_{gt} of each individual gt , select non-repeating individuals and put them into the set P_{gt}^* in descending order of crowding degree, put repeating individuals into the set $P_{gt}^{\#}$, keep traversing until the sum of both sets meets the required size N_{next} for the next generation P_{next} .

Step 2: Record the number of individuals N_{gt^*} in the set P_{gt}^* , then select additional N_{gt^*} non-repeating individuals from those remaining individual set $\blacktriangle$ after Step 1 and put them into set $P_{gt}^{\#}$.

Step 3: Set the probability of a certain individual k^* being selected from set P_{gt}^* as P_{pick}^* , in which, dj and cf are weight parameters controlling the influence of non-dominance rank and repetition level, with their sum equals to 1, ensuring that individuals with higher non-dominance ranks and greater repetition levels are more likely to be selected. In this paper, the selection probability for individuals in $P_{gt}^{\#}$ is set as $1 - P_{pick}^*$.

Step 4: Then select $N_{gt^*}/2$ individuals each from set P_{gt}^* and set $P_{gt}^{\#}$, and place them in the next generation population P_{next} . If N_{gt^*} is odd, then select an additional individual from set P_{gt}^* . The final number of individuals in the population P_{next} must be equal to N_{next} .

By appropriately retaining and discarding duplicate individuals, the proposed hierarchical graded preservation strategy enables the improved NSGA-II algorithm to retain

elite individuals while also providing previously discarded individuals with an opportunity to survive. Consequently, the quality and diversity of the next-generation population are both substantially improved, thereby alleviating the risk of premature convergence.

4.3. Solution Flow Design

The procedure of the improved NSGA-II algorithm is as follows:

Step 1: Initialize the population. Configure the population size N , iteration counter, maximum number of iterations, initial crossover probability, initial mutation probability, ammunition support information, operation procedure data and precedence constraints, and the number of personnel in each support category. Generate the initial population according to the encoding logic.

Step 2: Decode the chromosome strings to obtain the objective function values—ammunition support completion time and personnel workload balance. Perform non-dominated sorting of individuals based on these function values.

Step 3: Apply tournament selection, multi-point crossover, multi-point mutation, and the improved elitist preservation operation to the parent population to generate the offspring population. Decode the offspring to obtain their objective function values.

Step 4: Merge the parent and offspring populations into a combined population. Perform non-dominated sorting and crowding distance calculation and ranking on the combined population.

Step 5: Apply the improved elitist preservation operation to select N individuals from the combined population as the elite set for the next iteration.

Step 6: Increment the iteration counter by 1. If the maximum number of iterations has been reached, output the Pareto-optimal solution set and terminate; otherwise, return to Step 3.

4.4. Personnel Allocation and Operation Optimization Model

The purpose of personnel allocation decision-making is to optimize the staffing levels and identify the configuration that best supports scheme decision-making requirements. Given the professional matching constraints between personnel qualifications and operation procedures, the research question becomes: under the premise of ensuring task completion, which category of support personnel, when increased, yields the greatest benefit for scheme evolution. Su Xichao et al. [41] proposed a marginal optimization algorithm that addresses this class of problem progressively: by sequentially incrementing the head-count of each support group and comparing the resulting marginal benefit, the group whose personnel addition produces the maximum marginal benefit is identified. The marginal benefit increment employed in this paper is defined as:

$$BC^g = \max(\Delta C_\omega^g) \quad (12)$$

$$\Delta C_\omega^g = x_1 \left(T_{\min}^{g-1} - T_{\min}^g(N_\omega + 1) \right) + x_2 \left(G_{\min}^{g-1} - G_{\min}^g(N_\omega + 1) \right) \quad (13)$$

$$x_1 + x_2 = 1 \quad (14)$$

where g denotes the iteration count; $T_{\min}^{g-1}$ and $G_{\min}^{g-1}$ are, respectively, the ammunition support completion time and support personnel workload balance value under the personnel configuration at the k th iteration; the subtracted terms represent the corresponding values after adding one member to the targeted support group; and x_1 and x_2 are the marginal benefit weights for the two objectives, satisfying $x_1 + x_2 = 1$, $0 \leq x_1, x_2 \leq 1$.

4.5. Scheme Optimization Decision Feedback Model

The scheme optimization decision model takes the support personnel configuration as input and employs the improved NSGA-II algorithm proposed in this paper to derive the optimal personnel scheduling scheme for intermediate ordnance staging deck ammunition support operations. The resulting ammunition support completion time and personnel workload balance are fed back to the personnel allocation decision model, which iteratively compares the marginal benefit increment until the increment no longer justifies additional personnel. The steps are described as follows, with the corresponding flowchart shown in Figure 4.

Step 1: Set the initial iteration count $g = 0$ and the minimum marginal benefit increment threshold BC_{min} . Using the personnel quantity prediction model, configure the initial number of members in each support group.

Step 2: Apply the improved NSGA-II algorithm to compute the objective function values T_{min}^g and G_{min}^g under the initial personnel configuration.

Step 3: Sequentially increment the number of personnel in each ammunition support group and compute the marginal benefit increment BC^g .

Step 4: Select the support group with the largest marginal benefit increment BC^g , increase its personnel count by 1, and update the iteration count $g++$.

Step 5: Compare BC^g against BC_{min} . If $BC^g < BC_{min}$, terminate the algorithm and output the current optimal result; otherwise, return to Step 3.

The personnel quantity prediction model referenced above follows the occupied-type support resource prediction model established by Guo Linhan et al., expressed in Equation (15):

$$N_{\omega} = \left\lceil \varphi \times \frac{\sum_{i=1}^I \sum_{j=1}^J N_{ij\omega} \times t_j}{T_{min}^F} \right\rceil \quad (15)$$

where t_j denotes the standard operation time of the j th ammunition support operation procedure, T_{min}^F denotes the duration of the longest operation chain among the ammunition rounds to be supported, and φ denotes the personnel intensity coefficient under the current configuration.

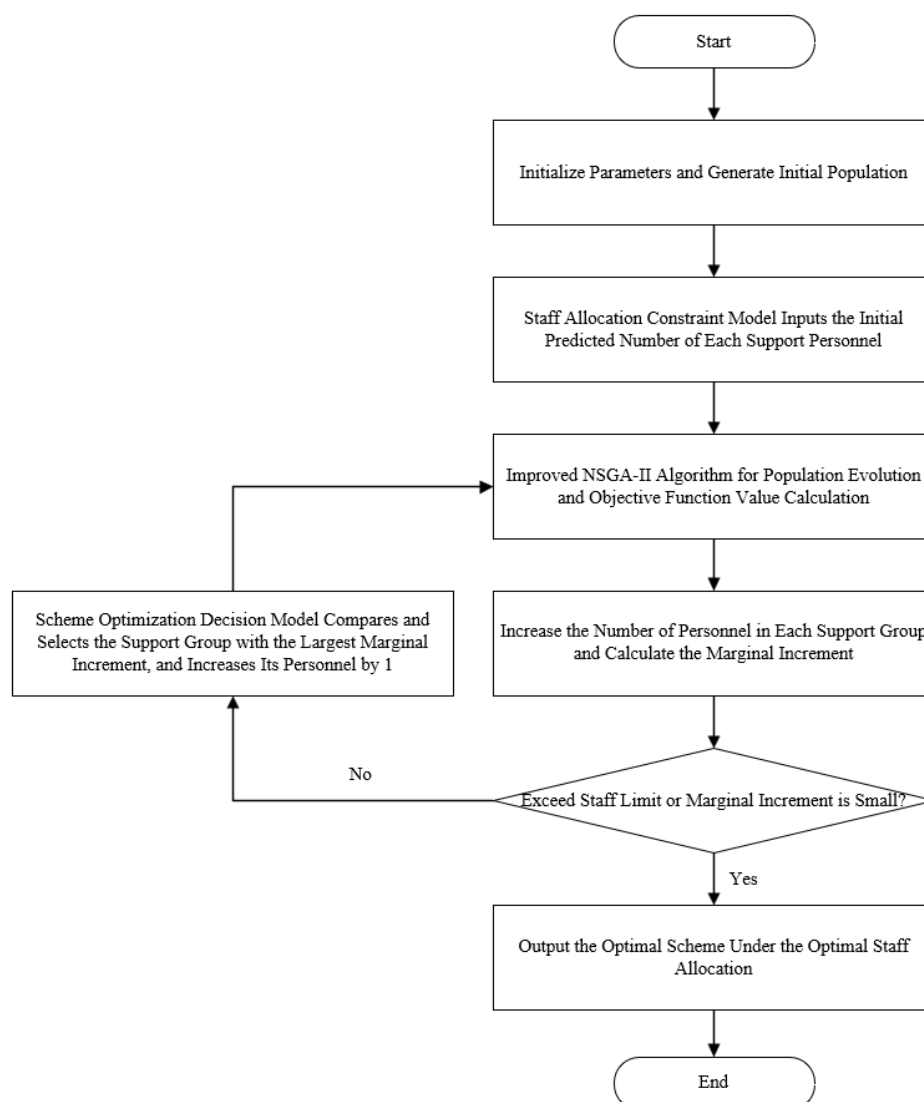


Figure 4. The improved NSGA-II algorithm process based on the staffing and operation scheme optimization model.

5. Simulation Experiments

5.1. Experimental Design

To validate the effectiveness of the proposed improved NSGA-II algorithm and the personnel allocation and operation scheme optimization model, a representative intermediate ordnance staging deck ammunition support operation scenario was constructed based on the baseline ammunition support requirements of an American-style aircraft carrier. All ammunition rounds are assumed to follow identical support operation procedures, with differences across ammunition types disregarded. The required support personnel categories and standard operation times for each intermediate ordnance staging deck ammunition support procedure are detailed in Table 2. Guidance device installation and fuze installation demand advanced professional competence and are therefore assigned one dedicated support member each from the ammunition electromechanical group and the assembly group.

The parameters of the improved NSGA-II algorithm are listed in Table 3. To ensure the applicability of the improved NSGA-II algorithm to the ammunition support operation scheduling problem on the transfer deck studied in this paper, the algorithm parameters listed in Table 3 were determined by first referring to the commonly used parameter

ranges reported in the literature [16,40] and then identifying the optimal combination through multiple experiments. Specifically, the candidate ranges of parameters, including population size, maximum number of iterations, crossover probability, and mutation probability, were initially determined with reference to the commonly adopted settings in NSGA-II algorithms and flexible jobshop scheduling problems. Subsequently, considering the characteristics of the proposed problem—namely, that the chromosome length is jointly determined by the number of ammunition items and the number of support procedures, and that the decoding process must simultaneously satisfy operation precedence constraints and personnel specialty matching constraints—multiple independent runs were conducted under different parameter combinations. Finally, the parameter values in Table 3 were determined based on algorithm convergence stability, the distribution of the Pareto solution set, the completion time of ammunition support operations on the transfer deck, the workload balance of support personnel, and computational time.

Table 2. Standard time and personnel quantity requirements for ammunition support operations.

Procedure No.	Procedure Name	Predecessor	Standard Time (s)	Required Personnel	Support Team
1	Ammunition Identification	/	60	1	Aviation Ordnanceman Crew
2	Ammunition Recording	1	60	1	Ordnance Documentation Crew
3	Ordnance Offloading from Lower Elevator	1	120	1	Weapons Handling Crew
4	Transfer to Assembly Station	2, 3	240	1	Weapons Handling Crew
5	Mission Parameter Input	4	360	1	Aviation Ordnanceman Crew
6	Component Verification	4	240	1	Aviation Ordnanceman Crew
7	Appearance & Interface Inspection	4	360	2	Ordnance Assembly Crew
8	Tail Fin Installation	6	600	1	Ordnance Assembly Crew
9	Guidance System Installation	6	1200	2	Ammunition Mechanic/Assembly Team
10	Data Recording	7	120	1	Ordnance Documentation Crew
11	Fuze Installation	8,9	800	2	Ammunition Mechanic/Assembly Team
12	Ammunition Testing	5, 10, 11	600	1	Aviation Ordnanceman Crew
13	Transfer to Upper Deck	12	240	1	Weapons Handling Crew

Table 3. Parameter settings of the improved NSGA-II algorithm.

Parameter Symbol	Parameter Description	Parameter Value
dj	Individual Non-Dominated Rank Weight	0.8
cf	Individual Duplication Degree Weight	0.2
tc_{max}	Maximum Number of Iterations	200
tc	Adaptive Iteration Threshold	150
N/N_{next}	Initial Population Size/Next-Generation Population Size	100
P_c	Initial Crossover Probability	0.4
σ	Crossover Probability Adjustment Coefficient	0.2
ϑ	Crossover Locus Linearity Adjustment Factor	0.5
P_B	Initial Mutation Probability	0.2
ϕ	Mutation Probability Adjustment Coefficient	0.1
γ	Mutation Locus Linearity Adjustment Factor	0.5

5.2. Experimental Results Analysis

This section first verifies the feasibility of the improved NSGA-II for solving the intermediate ordnance staging deck ammunition support operation problem. On this basis,

the personnel allocation and operation scheme optimization model is introduced to determine the optimal personnel configuration for each support group under a specified ammunition support mission.

21. Algorithm Comparison Analysis

Before proceeding to personnel allocation experiments, the feasibility of the improved NSGA-II is verified through comparison with the standard NSGA-II, Multi-Objective Ant Colony Optimization (MOACO), and Multi-Objective Particle Swarm Optimization (MOPSO) under identical parameter settings. The initial staffing of each support group is set as: electromechanical group 4, assembly group 4, transport group 2, and recording group 1. The number of ammunition rounds to be supported is 2, both arriving at the intermediate ordnance staging deck simultaneously at time zero. The iterative comparison charts for the two objective functions—shortest support operation time and personnel workload balance—are shown in Figures 5 and 6.

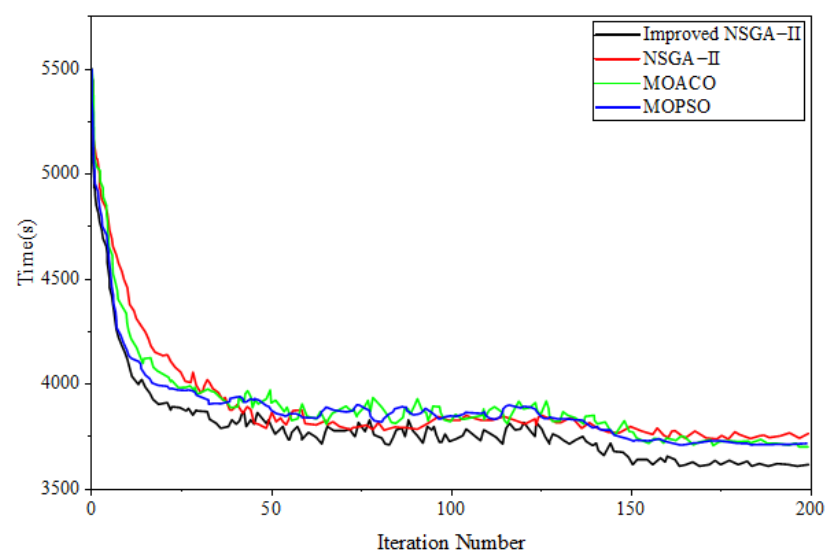


Figure 5. Iteration of shortest support operation time.

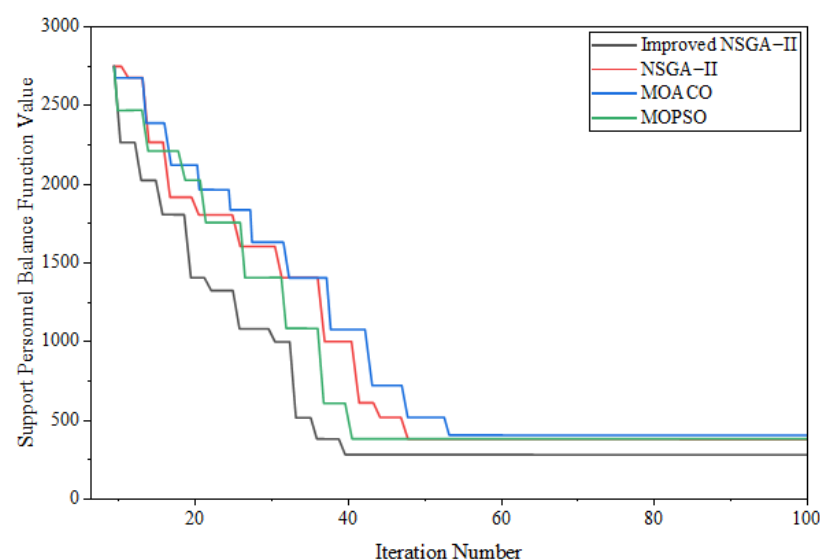


Figure 6. Iteration of support personnel workload balance.

From the results shown in Figures 5 and 6, it can be observed that during the population iteration process for the two objectives—ammunition support operation time and workload balance of support personnel—all four algorithms, namely improved NSGA-II,

standard NSGA-II, MOACO, and MOPSO, exhibit a decreasing trend with fast convergence in the early stage, followed by gradual fluctuations near the Pareto-optimal solutions. Among them, the improved NSGA-II converges fastest and achieves the best final value for the operation time objective.

In terms of fluctuation characteristics, the objective values of the improved NSGA-II fluctuate more violently than those of the other algorithms. This is because the improved NSGA-II employs an adaptive probability mechanism during crossover and mutation operations: when the evolutionary direction is not yet determined, the crossover probability is increased to accelerate convergence; after the direction is established, the mutation probability is raised to expand the search breadth. Consequently, the algorithm maintains a greater search breadth throughout the entire iteration process. In contrast, MOACO and MOPSO, which rely on pheromone or particle swarm updates, adopt strategies that emphasise local exploitation, resulting in smaller fluctuations but relatively limited optimisation capability in terms of operation time. In addition, the inherent conflict between objectives in multi-objective optimisation often leads to repeated changes in solutions, which is also an important reason for the observed fluctuations.

To mitigate the effect of random variation, ten independent experiments were conducted for the above case, and the results were analyzed across three dimensions: Pareto-optimal solution quality, quantity, and solution time. The comparison results are shown in Table 4. The data indicate that although the improved NSGA-II is marginally inferior in the count of optimal solutions, it outperforms the other three algorithms in both objective function values and computation time.

Based on the comparison of objective function values shown in Table 4, to further quantitatively evaluate the overall quality of the Pareto solution sets obtained by each algorithm, this paper introduces the hyper-volume (HV) indicator. In the calculation, all non-dominated solutions from a total of 40 experiments conducted with the four algorithms are merged, and the maximum observed value of each objective is taken as the reference point. The objective space is then linearly normalised and the normalised HV value is computed. The comparison of the mean HV values from 10 independent runs of each algorithm is presented in Table 5. The results show that the mean HV of the improved NSGA-II proposed in this paper is higher than that of the other three compared algorithms, indicating that its Pareto solution set achieves the best overall performance in terms of both convergence and diversity. This further verifies the effectiveness of the improvement strategies adopted in this paper.

Table 4. Comparison of experimental results.

Algorithm Name	Comparison Metric	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	Experiment 6	Experiment 7	Experiment 8	Experiment 9	Experiment 10	Mean
Improved NSGA-II	$\min T_{max}$	3600	3600	3720	3660	3600	3680	3620	3600	3660	3600	3634
	$\min G$	286	284	286	312	284	286	288	286	290	284	288.4
	Number of Optimal Solutions	5	6	4	5	5	6	5	5	5	6	5.4
	Computation Time (s)	74	77	74	76	75	73	76	74	75	74	74.8
NSGA-II	$\min T_{max}$	3720	3860	3780	3720	3720	3740	3800	3760	3700	3780	3758
	$\min G$	286	406	346	286	294	310	356	300	286	320	319
	Number of Optimal Solutions	8	6	8	6	6	7	6	8	7	7	6.9

MOACO	Computation Time (s)	68	72	66	68	75	70	69	67	71	68	69.4
	min T_{max}	3840	3820	3860	3800	3840	3850	3810	3830	3860	3820	3833
	min G	398	385	392	406	389	395	388	402	391	397	394.3
	Number of Optimal Solutions	4	6	4	5	4	4	6	4	5	5	4.7
	Computation Time (s)	48	52	46	50	49	47	51	48	50	49	49
MOPSO	min T_{max}	3700	3740	3720	3680	3740	3710	3750	3690	3730	3720	3718
	min G	312	308	320	305	315	310	325	302	318	311	312.6
	Number of Optimal Solutions	6	7	5	6	6	7	5	6	6	7	6.1
	Computation Time (s)	70	74	71	69	72	70	73	69	72	71	71.1

Table 5. Comparison of normalized HV metrics.

Algorithm Name	Experiment 1	Experiment 2	Experiment 3	Experiment 4	Experiment 5	Experiment 6	Experiment 7	Experiment 8	Experiment 9	Experiment 10	Mean
Improved NSGA-II	0.785	0.795	0.775	0.777	0.790	0.786	0.782	0.792	0.78	0.788	0.789
NSGA-II	0.755	0.742	0.748	0.762	0.756	0.75	0.741	0.758	0.765	0.748	0.757
MOACO	0.715	0.720	0.712	0.718	0.716	0.714	0.719	0.71	0.715	0.717	0.718
MOPSO	0.762	0.758	0.755	0.768	0.76	0.763	0.752	0.77	0.758	0.761	0.765

Figure 7 presents the ammunition support personnel scheduling Gantt chart obtained by the improved NSGA-II in the second experiment. The numbers within the white blocks consist of two segments, displayed in the format “ammunition index-ammunition operation procedure index” to denote the operation content. For example, ‘2-8’ in Figure 7 means the eighth ammunition operation procedure for the second ammunition. Under this scheme, the ammunition support operation completion time is 3600 s and the support personnel workload balance value is 284. The simulation results show that the operation precedence satisfies the standards prescribed in the ammunition support procedures; series and parallel procedures are free of mutual interference, and personnel task allocation has achieved balance. These findings confirm the feasibility of the improved NSGA-II for the intermediate ordnance staging deck ammunition support problem.

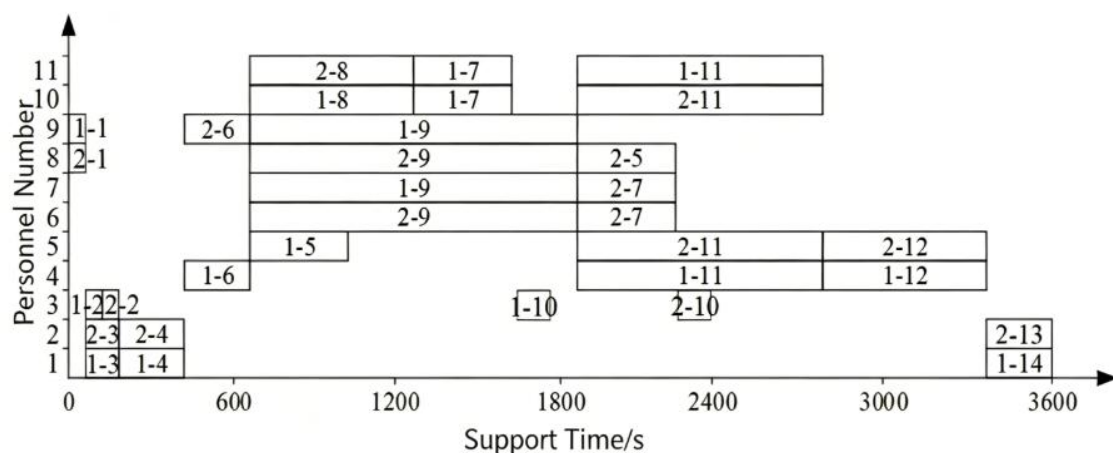


Figure 7. Gantt chart of two ammunition support operations.

22. Optimal Configuration Analysis of Support Personnel

The research objective of this paper extends beyond minimizing ammunition support operation time to encompass the optimal configuration of personnel across all support groups. Accordingly, the personnel allocation and operation scheme optimization model is experimentally validated. Keeping the parameters of the improved NSGA-II unchanged, the number of ammunition rounds to be supported is increased to 4, and the relevant model parameters are set as shown in Table 6. The initial staffing of each support group is obtained from Equation (15). Given the specific nature of the operational scenario investigated in this study, time is the primary factor to be guaranteed, followed by personnel balance. Therefore, based on expert advice, the marginal benefit weights for $T_{\min}^g$ (x_1) and $G_{\min}^g$ (x_2) are set to 0.6 and 0.4, respectively. To capture the trend of personnel configuration without exceeding the optimal allocation range, the personnel intensity coefficient φ is set to 6.

Table 6. Parameter settings of the scheme optimization decision feedback model.

Parameter Symbol	Parameter Meaning	Parameter Value
BR	Number of Support Personnel	[10, 20]
x_1	Marginal Benefit Weight of $TT_{\min}^g$	0.6
x_2	Marginal Benefit Weight of $AG_{\min}^g$	0.4
$BC_{\min}$	Minimum Marginal Benefit Increment	1
φ	Personnel Intensity Coefficient	6

The task information and parameter values were input into the model, and the results are shown in Figure 8. The figure illustrates the personnel allocation optimization process under the specified ammunition support mission requirements. Beginning from an initial total of 10 personnel, both the support personnel workload and the support operation completion time exhibit an overall downward trend as the headcount increases. Although the marginal gain fluctuates considerably in magnitude, it remains consistently above the preset minimum threshold. When the total personnel count reaches 20, the marginal benefit drops to zero, at which point the personnel configuration represents the optimal allocation scheme.

Changes in the staffing of each support group during the optimization process are depicted in Figure 9. The computed initial personnel configuration is [4, 4, 1, 1]. After algorithm optimization, the optimal configuration is [8, 6, 4, 2]—a net increase of 10 support personnel—with the ammunition assembly group and ammunition transport group accounting for the most substantial increases.

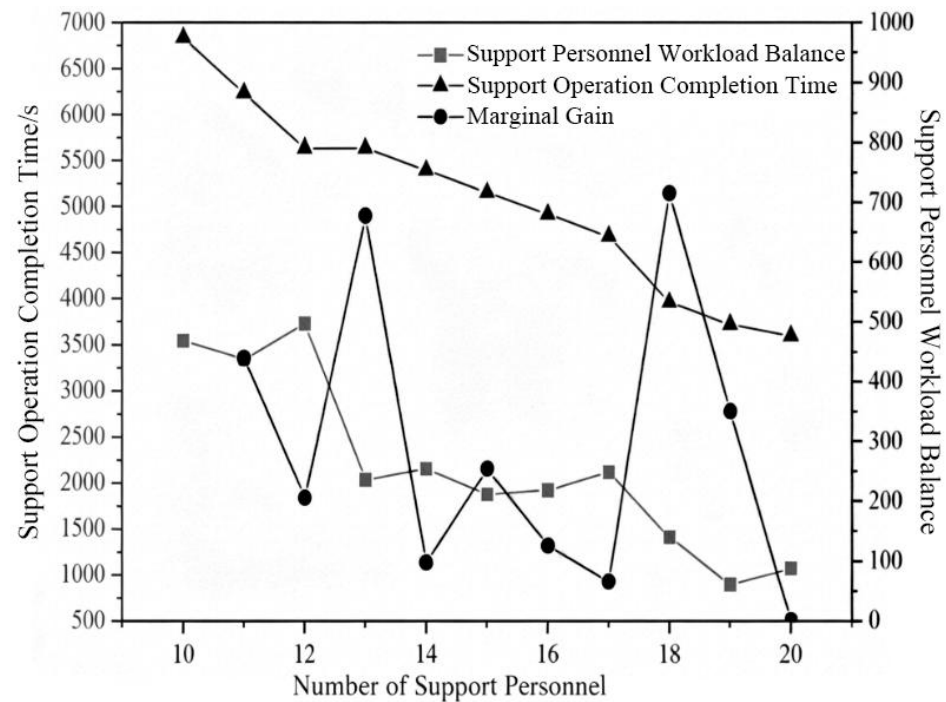


Figure 8. Optimization of support personnel configuration.

Closer examination reveals that the earliest personnel additions and those yielding the highest marginal gains both belong to the ammunition transport group. Although the standard operation time for ammunition transport is relatively brief, the transport procedures occupy critical nodes within the series-parallel procedure network, spanning the entire support process. Most subsequent procedures cannot proceed until ammunition has been transported into position. Prioritizing personnel additions to the ammunition transport group therefore accelerates the throughput of the entire operation.

The ammunition assembly group registered the largest personnel increase, gaining 4 additional members. This reflects the relatively long duration of assembly procedures and the group's mid-flow position in the operation sequence, which together demand a larger workforce to share the load. Moreover, the third incremental addition was allocated to the assembly group. Although this addition did not markedly shorten the support operation completion time, the introduction of an additional assembly worker substantially improved personnel workload balance; the algorithm accordingly made this allocation at a relatively early stage. These observations are consistent with operational reality and offer useful practical guidance for real-world personnel configuration optimization.

Figure 10 shows the Gantt chart of the ammunition support operation scheme under the optimal personnel configuration. The meaning of the number combination is the same to Figure 7. Under this scheme, the support operation completion time is 3600 s and the personnel workload balance value is 1075. Despite the increase in the number of ammunition rounds, the rational configuration provided by the personnel allocation and operation scheme optimization model successfully compressed the support operation time to the same level as that required for two ammunition rounds. In terms of personnel workload balance, task allocation across all support groups is reasonably distributed, and both the continuity and the concentration of the overall operation are markedly improved. These results attest to the scientific rigor and effectiveness of the model in handling increased mission demands.

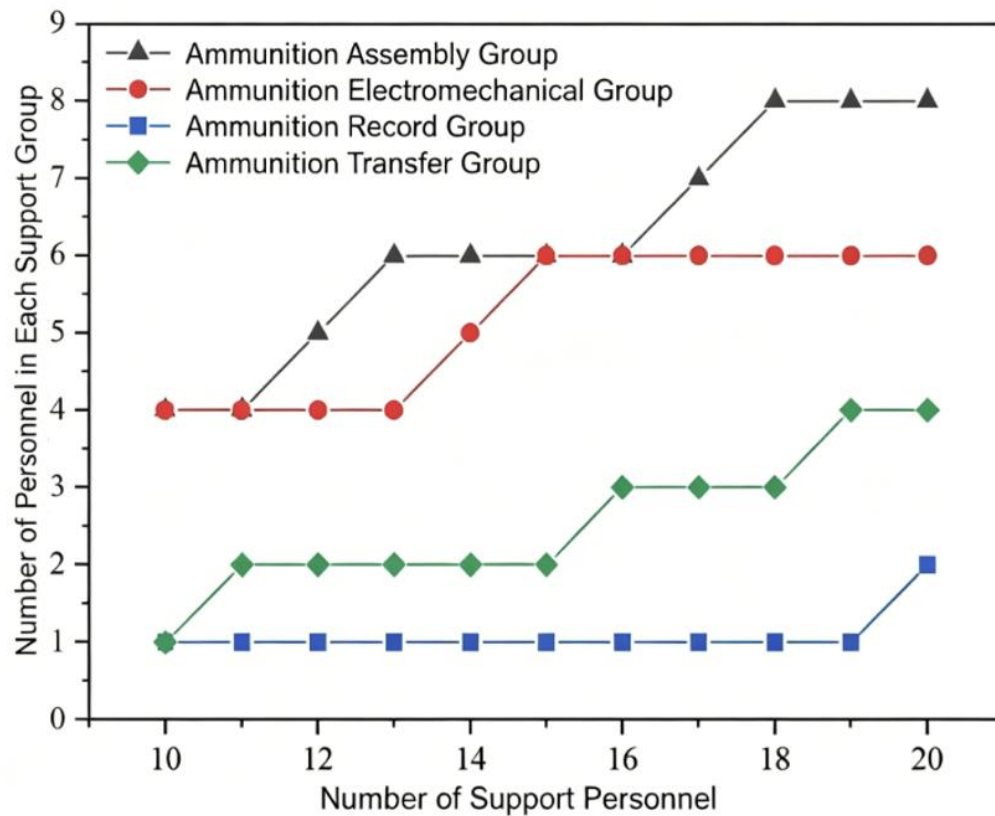


Figure 9. Changes in the number of various types of support personnel.

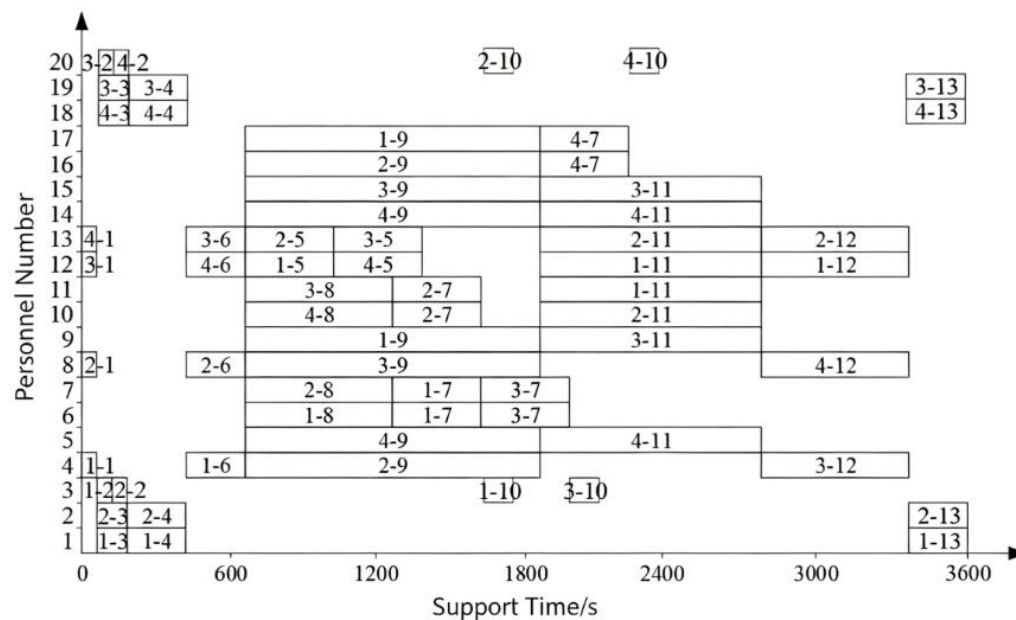


Figure 10. Gantt chart of ammunition support operations under optimal personnel configuration.

The improved NSGA-II algorithm yields a Pareto-optimal solution set rather than a unique definitive solution. The various solutions exhibit a trade-off relationship between ensuring operational completion time and personnel workload balancing. Therefore, the final implementation plan must be determined based on decision preferences. In practical applications, the weighted sum method can be employed to select the optimal compro-

mise solution, with the weight allocation flexibly adjusted according to operational requirements. When the deck operation window is tight, priority should be given to the time-related criterion; when sustained operations require avoiding excessive crew fatigue, emphasis should be placed on the workload balancing criterion.

6. Conclusions

This paper has investigated the personnel allocation and scheduling optimization problem for ammunition support operations on the carrier-based aircraft intermediate ordnance staging deck. By improving the NSGA-II algorithm and constructing a constraint decision model, multi-objective optimization encompassing both operation time minimization and personnel workload balancing was achieved. The main contributions and conclusions are as follows.

Model construction and algorithm improvement: The intermediate ordnance staging deck ammunition support operation was abstracted as a multistage, multi-constraint job shop scheduling problem, and a bi-objective optimization model was formulated with support time and personnel workload balance as the core objectives. To address the limitations of the standard NSGA-II in maintaining population diversity, the elitist preservation strategy was enhanced and an adaptive crossover and mutation mechanism was introduced, improving both convergence behavior and solution set quality. Simulation experiments confirm that the improved algorithm surpasses the standard method in terms of both solution speed and Pareto front distribution.

Personnel allocation optimization: A progressive personnel allocation optimization strategy based on marginal benefit analysis was proposed, enabling dynamic adjustment of staffing levels across support groups (transport group, electromechanical group, etc.). Experimental results demonstrate that the optimal configuration (e.g., electromechanical group 8, assembly group 6) reduces the operation time to 3600 s for 4 ammunition rounds while lowering the personnel workload balance value to 1075, thereby validating the practical utility of the model.

Limitations and future directions: (i) Dynamic environment adaptability: the current model assumes a static operating environment and does not account for uncertainty factors such as emergent tasks or equipment failures; future work may incorporate robust optimization or online scheduling methods. (ii) Multistage collaborative optimization: this paper focuses on the intermediate ordnance staging deck as an isolated stage, whereas actual ammunition support involves coordinated operations across the magazine, flight deck, and other layers; subsequent research may extend to full-process integrated scheduling. (iii) Algorithm generalization: the improved NSGA-II performs well in the specific scenarios, but further validation of its generalizability to other complex operations, such as mixed support of multiple ammunition types, is required by increasing the sample size.

In summary, this study provides a scientifically grounded scheduling methodology and configuration strategy for carrier ammunition support. Future integration of dynamic response mechanisms and intelligent decision-making techniques can further enhance the model's applicability to real combat environments.

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Data Availability Statement: The data used in this study were obtained from a mission-oriented supply support scenario and contain sensitive operational information. Due to confidentiality restrictions, the original datasets cannot be made publicly available. The data supporting the findings of this study are available from the corresponding author upon reasonable request, subject to institutional approval and data protection regulations.

Conflicts of Interest: The authors declare no conflicts of interest.

Statement Regarding Dual-Use Research of Concern: Current research is limited to the optimization scheduling field of shipborne aircraft intermediate ordnance staging deck ammunition support operations, which is beneficial to improve the efficiency of carrier aviation ammunition supply and the rationality of personnel allocation, and does not pose a threat to public health or national security. Authors acknowledge the dual use potential of research involving naval equipment operation scheduling algorithms and resource allocation models, and confirm that all necessary precautions have been taken to prevent potential misuse. As an ethical responsibility, authors strictly adhere to relevant national and international laws about DURC. Authors advocate for responsible deployment, ethical considerations, regulatory compliance, and transparent reporting to mitigate misuse risks and foster beneficial outcomes.

Abbreviations

The following abbreviations are used in this manuscript:

AAM	Air-to-Air Missile
AGM	Air-to-Ground Missile
ASM	Air-to-Ship Missile
FJSP	Flexible Job Shop Scheduling Problem
MOEA/DM	Multi-objective Evolutionary Algorithm Based on Decomposition
NSGA-II	Non-dominated Sorting Genetic Algorithm II

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