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Integrated scheduling method for fleet wave sorties and maintenance of naval distributed platforms

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ABSTRACT

Managing operational command and maintenance support activities for carrier-based aircraft in a multi-platform system is challenging. This research presents an integrated mathematical model for scheduling deployment, sortie, and maintenance of carrier-based aircraft. The model helps decision-makers formulate fleet allocation plans, create sortie flight schedules, and coordinate repairs for future maritime distributed operations. We have introduced a novel bi-level iteration optimization method that improves traditional manual empirical scheduling methods. An advanced version, a two-stage optimization method, can handle a large number of states and solution spaces while ensuring accuracy. Our statistical validation shows that the two-stage optimization method has an insignificant deviation of 1–2% (with an average of −0.91%) from accurate results. Importantly, this method significantly reduces computational time (with an average of 98.25%), which enhances decision-making accuracy and real-time feasibility. Finally, the research discusses a cross-platform linkage mechanism for distributing aircraft repair tasks. This mechanism aims to enhance mission readiness and operational metrics by avoiding backlogs and reducing inefficiencies caused by concentrating maintenance on a single platform. The results of this study provide a foundation for decision-making regarding future naval distributed systems and their operations.

1. Introduction

1.1. Background introduction

Large surface vessels, such as aircraft carriers, are valuable for distant sea operations. They can be deployed forward across global maritime domains to perform tasks such as sea control and power projection. The primary weaponry on aircraft carriers is carrier-based aircraft, which are essential for tasks like maritime blockades and strikes against coastal targets. These aircraft have high-speed maneuverability and three-dimensional attack capabilities that facilitate strategic de-escalation in naval warfare, leading to the acquisition of regional air and sea control. The combat capabilities of aircraft carriers depend directly on the quantity, performance, and sortie rate of their carrier-based aircraft, and their sortie and recovery capacity is crucial.

The wave sortie flight planning of carrier-based aircraft must meet the demands of large-scale, high-intensity, and sustained combat missions. Maintenance and support work is crucial to ensure they are always ready for these missions. This work restores and maintains the aircraft's optimal technical condition, improves fleet readiness, and provides essential support for various flight missions, including combat readiness, training, and operations. The maintenance also ensures the safety and reliability of carrier-based aircraft during mission execution, which is vital for their combat capability.

To make maintenance and support of carrier-based aircraft effective, resources must be allocated scientifically and rationally. The allocation should include temporal planning (scheduling) of aircraft, relevant support personnel, and facilities in the complex deck environment. This planning aims to shorten operational time, increase sortie rates, and optimize associated efficiency metrics. The goal is to achieve coordinated, safe, and efficient operations at each stage, thereby improving the aircraft fleet's sustained combat capability. As the intensity of operations and training increases, these constraints become more prominent, affecting the overall operational effectiveness of the platform [1].

The effectiveness of maintenance and support capabilities and operational modes are interdependent. In the current era of

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informationized battlefields, systematic warfare is the primary combat paradigm. Recent years have seen the emergence of concepts like "Distributed Maritime Operation," "Multi-domain Operation," and "Mosaic Warfare," which have led to the development of agile and flexible systemic capabilities. Distributed warfare units, characterized by flexible mobility and real-time reconfigurability, are redefining naval warfare. These units exhibit the characteristics of dispersed forces and concentrated firepower, influencing the adversary's perception, decision-making regarding strike targets, and cost calculations, thereby gaining battlefield advantages. However, this advantage poses a formidable challenge to traditional centralized large fleet formation warfare models.

Innovative operational concepts drive equipment evolution. In complex and dynamic operational environments, systems must respond with agile, rapid, and customized task fulfillment to unleash nonlinear operational effectiveness. In the future, the number and scale of carrier-based aircraft on aircraft carriers of various nations will increase, and the styles of participating operations will become more complex and diverse. However, the decision-making for distributed platforms involves numerous and complexly configured aircraft groups, significant differences in deployment scale and patterns, and dynamic solid characteristics. These challenges pose difficulties in efficiently commanding operations and managing maintenance and support for aircraft groups. The reliance on experience-based manual scheduling is increasingly inadequate to meet the demands of reliability and timeliness [2].

The main issue we aimed to address is "providing decision makers with an integrated scheduling mathematical model for the deployment, combat, and dynamic maintenance of carrier-based aircraft (This is similar to the manufacturing industry's challenge of coordinating production and maintenance schedules). The goal is to create practical plans that improve specific performance measurements while meeting time and resource restrictions.

However, the assumption that all the project information and data are known a *priori* often does not hold. Scheduling requires quick replanning, which involves replanning operations. Deck supervisors must balance the conflicting directives of maximizing safety and minimizing operational time. Similarly, during high-occupancy and time-critical cases like natural disasters, allocating hospital operating rooms requires immediate action. Therefore, under the concept of distributed maritime operations, the following issues must be considered:

(i) The allocation of platforms and plan sortie planning for the participating units.
(ii) The integration of maintenance resources among platforms, dispersion of the maintenance load, and improvement in unit availability and combat effectiveness.
(iii) The approach to realizing synergy, efficiency, and orderly distributed-platform deployment and maintenance tasks.

One of the biggest challenges in decision-making is not only choosing which project to start, but also deciding which projects to delay or interrupt when resources are limited. In this context, we have tackled the problem of dynamic scheduling of resource-constrained projects. We explored a new instance of this problem domain in the aircraft carrier flight deck. To address the complexity of this problem, we developed a novel model with state-of-the-art algorithms, which enables us to handle a large number of states and solutions efficiently.

1.2. Current research status

Currently, researchers are only beginning to investigate the combination of fleet-wave sorties and maintenance scheduling for carrier-based aircraft. Most investigation results from civil aviation can be used as a reference. In fact, investigations in this field are primarily focused on two types of problems: the aircraft task allocation problem (TAP) and aircraft maintenance planning (AMP) [3]. Most existing studies solve flight planning and maintenance scheduling problems sequentially via multistep optimization. This multistep approach yields an overall suboptimal solution [4]. Safaei et al. [5,6] highlighted that existing strategies and practices lack the integration of the TAP and AMP, and that they must be unified in the same framework for interaction. The abovementioned problem appears in existing hangar-deck operation processes as well. Hence, Deng et al. [7] proposed a novel decision-support system for optimizing task allocation and aircraft maintenance inspection planning to optimize aircraft maintenance task assignments. Eltoukhy et al. [8] proposed a bi-level optimization model for aircraft maintenance planning and personnel and used a bi-level nested ant colony optimization algorithm to solve it. Lin et al. [9] proposed an algorithm inspired by the yeast reproduction process to develop a bi-level model based on fleet maintenance with the objectives of minimizing the maximum makespan, balancing the number of hangar bay resources, and reducing the fleet maintenance cost. Bi-level scheduling has numerous applications in the field of maintenance reliability, such as joint bidding and maintenance scheduling of generation units [10], consulting relief for multi-modal urban transit network design [11], and maintenance scheduling of manufacturing systems [12], among others. *The recent scholarly works highlight the ascendance of concurrent optimization in maintenance and production scheduling within manufacturing systems as a focal point of research* [13,14]. *Advanced optimization methodologies have been formulated to tackle the inherent NP-hard complexity of this domain* [15]. *For instance, Sharifi et al.* [16]*pioneered a study that jointly optimizes production schedules and maintenance plans in a parallel-machine production setting. They employed a robust genetic algorithm to address this novel problem effectively.* It's worth noting that the ideas mentioned above haven't been implemented in the field of military aviation maintenance. Naval aircraft flight planning and maintenance scheduling investigations are still in the independent development phase. Like in manufacturing, maintenance activities for aircraft also take up a considerable amount of time. That is to say, only considering flight planning or maintenance planning is out of touch with the operational mission [17]. It is important to note that naval aircraft operate differently from civil aviation. They fly in a cluster wave sortie and use a recovery mode with shorter and more frequent maintenance cycles. The maintenance resources available in the hangar bays are limited and complex, and the goal is to optimize fleet operational efficiency rather than cost.

Theoretical studies on scheduling carrier-based aircraft sorties and recovery operations fall into two categories: full-process and phased operation scheduling [18]. For full-process operational scheduling, Ryan et al. [19] developed a deck-operations decision system based on human–computer interactions and designed a set of experiments to compare automatic planning algorithms with manual empirical decisions [20]. Accordingly, Michini et al. [21] proposed an inverse reinforcement learning method to imitate expert behavior and improve scheduling strategies. A real-time integrated information management system that includes the results of the aviation data management and control system (ADMACS) was proposed [22]. In recent years, phased operation scheduling of naval aircraft has emerged owing to related achievements. It includes several operation phases such as aircraft dispatch [23,24], weapon transportation support [25], flight deck operations [26,27], sorties and departures [28,29], landing and recovery [30], and maintenance and repair[31,32]. Flight planning is the basis for scheduling carrier-based aircraft operations. In a typical sortie mission, the commander first develops a sortie-flight plan based on empirical data. After that, the above-mentioned phase process operation scheduling is carried out sequentially. The sortie-flight plan can have a direct impact on the subsequent operational scheduling optimization. However, the existing studies are based on the optimal design of a given mission scenario, so the flight planning for fleet wave sorties is usually a known condition. Unfortunately, there is no established formula for sortie-flight planning. Due to the increased mission complexity and the trend of distributed operations, developing an efficient flight plan for

Table 1
A brief survey of the recent works on aeronautical maintenance and repair task scheduling problem.

Year	Authors	Application		Temporal attributes		Integrated scheduling?	Multi-platform coordination?	Scheduling models	Algorithm or procedure
		Civilian	Military	Static	Dynamic				
2011	Safaei et al. [33]	×	√	√	×	×	×	Mixed-integer programming	Branch-and-bound method
2013	Han et al. [34]	√	×	√	×	×	×	Maintenance resources allocation model	Queuing theory
2014	Feng et al. [35]	×	√	√	×	×	×	3-layer multi-agent system	Contract net protocol algorithms
2017	Feng et al. [36]	×	√	√	×	×	×	Two-game approach framework	Heuristic hybrid game method
2018	Eltoukhy et al. [8]	√	×	√	×	√	×	Bi-level scheduling	Ant colony algorithm
2019	Lin et al. [9]	√	×	√	×	√	×	Bi-level scheduling	Propagation algorithm of yeast
2021	Tiantian et al. [32]	×	√	√	×	×	×	Modeling of part transportation	Takagi-Sugeno fuzzy robust control
2021	Deng et al. [7]	√	×	√	√	√	×	Top-down model layer	Decision support system
2021	Zeng et al. [37]	×	√	×	√	×	×	Statistical optimization model	Meta-heuristic algorithms
2021	Barahimi et al. [11]	√	×	√	√	√	×	Bi-level scheduling	Particle swarm optimization algorithm
2021	Sharifi et al. [13]	√	×	√	√	√	×	Joint production scheduling-maintenance optimization model	Meta-heuristic algorithms
2022	Rokhforoz et al. [12]	√	×	√	×	×	×	Bi-level scheduling	Leader and multiple-followers game
2022	Li et al. [31]	×	√	√	×	×	×	Maintenance and repair task scheduling model	Meta-heuristic algorithms
2023	Rokhforoz et al. [10]	√	×	√	×	×	×	Convert the bi-level to single level model	Multi-agent deep RL
2023	Zhang et al. [38]	×	√	√	√	×	×	Maintenance task scheduling model	Improved non-dominated sorting genetic algorithm II and reactive scheduling methods
2023	This paper	×	√	√	√	√	√	Integrated scheduling model for sorties and maintenance of distributed platforms	Bi-level and Two-stage optimization method

sorties to satisfy the requirements of manual empirical methods has become even more difficult [23].

In a theoretical study regarding the maintenance scheduling of carrier-based aircraft, Safaei et al. [33] elaborated on the military aircraft maintenance process and personnel constraints, as well as proposed a linear mixed-integer maintenance model. Han et al. [34] established a simplified personnel allocation model for military aircraft maintenance assurance and computed the model based on queuing theory. Feng et al. [35] proposed a multi-agent-based allocation method for fleet maintenance personnel, which can also provide optimal maintenance strategies compared with the conventional approach, which only includes allocation results. Feng et al. [36] proposed a heuristic hybrid game method to solve fleet condition-based maintenance planning. A hierarchical framework based on a set of dispatched and standby fleets was used, which significantly reduced the problem size. Zeng et al. [37] proposed a comprehensive availability constraint model by considering preventive maintenance and random fault repair times and used a heuristic algorithm to establish aircraft maintenance operation scheduling and equipment scheduling schemes. Zhang et al. [38] proposed a resource-constrained maintenance task scheduling model based on fleet wave availability and the load balance of maintenance personnel in the hangar bay as optimization indicators, as well as used a heuristic algorithm to solve the problem investigated. The above-mentioned studies focus on single-platform naval aircraft maintenance. Nonetheless, the complexity of modeling continues to increase; the abstraction of modeling has evolved from mathematical programming modeling to resource-constrained project scheduling problem modeling. Algorithms are gradually transformed from conventional optimization to *meta*-heuristic algorithms [39]. This study is inspired by the aforementioned studies. However, it similarly focuses on the static maintenance scheduling planning of a single platform. The dynamics and scalability in this field must be considered urgently to realize the dynamic maintenance interaction of distributed platforms to adapt to the development of distributed maritime operations in the future.

In a theoretical study pertaining to dynamic scheduling, Feng et al. [40] analyzed uncertainties, such as system and task disturbances, in the dynamic scheduling process of deck operations and maintenance. Stochastic damage simulation is a way of capturing uncertainty, particularly essential in carrier-based aircraft maintenance operations. The reason is straightforward: aircraft system or component failure appears to be random, while maintenance tasks are tightly coupled according to the networked precedence relations. The optimality of maintenance scheduling plans depends on the assumption that each maintenance operation in the baseline scheduling scheme is not advanced or delayed, and any disturbances during the maintenance task process, such as the inclusion of temporary tasks, may have a snowball effect on subsequent maintenance activities, causing the scheme to lose its optimality and leading to delays that require rescheduling. So, dynamic strategies are accessed to rearrange subsequent maintenance plans after disturbances occur [41,42]. Hence, Ouelhadj et al. [43] reviewed the dynamic scheduling problem in manufacturing and classified it into proactive, reactive, and robust scheduling. Depending on the objectives of scheduling and complex scheduling environments, reactive scheduling can be performed to modify scheduling based on specific interference factors, which is more practical than proactive scheduling. The disturbance events involved in the reactive scheduling theory and approach include various uncertainties, such as the inclusion of temporary tasks [44], delays in operations [45], and equipment faults [46]. An et al. [47] proposed two complete reactive scheduling strategies for addressing dynamic disturbances. The current approaches used in the dynamic

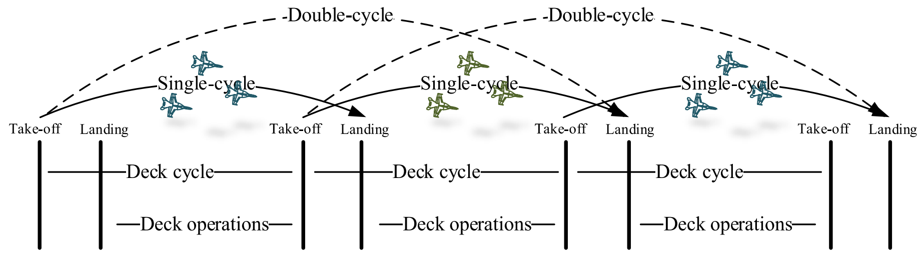


Fig. 1. Schematic illustration of single-cycle double-formation continuous sortie.

scheduling of carrier-based aircraft primarily include multi-agent systems [48], proactive robust scheduling [49], rolling horizon strategy reactive scheduling [50,51], heuristic rule-based complete reactive scheduling [20], and reinforcement learning scheduling [52]. The studies above provide ideas for dynamic maintenance scheduling.

A brief survey of the recent research(2011-now) about aeronautical maintenance and repair task scheduling problems is presented in Table 1. As shown in Table 1, an integrated scheduling method for fleet wave sorties and the maintenance of naval distributed platforms are modeled in this research. The model considers various processes, resources, and time constraints. Besides, the dynamic temporal attributes of integrated scheduling are also considered in this research. Under the condition of the disturbance of random faults or battle damage, allocation heuristic rules are proposed to realize the cross-platform linkage mechanism of carrier-based aircraft fault repair tasks and avoid the large-scale centralization of platform maintenance and repair tasks. Essentially, previous works have not addressed scheduling models and solutions that possess the attributes of being "military-application," "distributed," and "integrated" simultaneously.

To summarize, while previous studies have yielded some results, they have failed to address the following three deficiencies:

i. Flight planning is done through a manual, empirical process, and the current scheme is based on known input conditions. This means that there has been no consideration for an integrated scheduling decision that takes into account aircraft fleet sorties and preventive maintenance tasks.
ii. The scheduling of aircraft fleet sortie operations is focused solely on the conventional single-platform core ship in the centralized operational mode. The allocation of aircraft fleets to distributed platforms and the transfer of failed aircraft repair tasks in platform links have not been taken into account.
iii. The static scheduling of preventive maintenance plans is solved in a deterministic environment. This means that there has been no consideration for a dynamic correction adjustment of the maintenance scheduling scheme under conditions such as urgent demand for available aircraft, the continuous addition of failed aircraft, the concentration of hangar bay loads, and the disturbance in the maintenance scheduling process.

To tackle the issues mentioned earlier, this study proposes an integration of fleet sortie flight planning and maintenance scheduling on a distributed platform. The innovation lies in the following three aspects:

i. A systematic analysis of the distributed platform constraints of fleet allocation, sortie flight planning, continuous cyclic sortie operation rules, and preventive maintenance. This leads to the establishment of a static model for aircraft fleet sorties and the maintenance integrated scheduling problem of distributed platforms (DP-ASMS).
ii. Proposed optimization objectives for the DP-ASMS include the comprehensive effectiveness of distributed platform tasks, comprehensive effectiveness of a single platform task, completion rate of continuous cyclic sortie, dispersion rate of maintenance load, and completion rate of the wave continuous cycle. Two methods are proposed, i.e., the bi-level iteration optimization and two-stage optimization methods, using the surrogate function for fleet allocation on distributed platforms. Subsequently, the two optimization methods are compared and analyzed.
iii. The study simulates random faults or battle damage based on a distributed platform engagement, which involves static modeling and incorporating dynamic uncertainty disturbances. A cross-platform linkage mechanism with distributed repair task allocation heuristic rules is proposed to solve the DP-ASMS dynamic modeling. This results in a revised scheduling scheme for the fleet sortie flight planning and maintenance.

The paper is structured as follows: The next section presents problem statements related to the DP-ASMS, including continuous cyclic sortie operation rules, flight planning, maintenance and repair tasks, fleet allocation, and cross-platform linkage mechanisms, as well as methodology. Section 3 presents the constraints and optimization objectives of the mathematical formulation for the DP-ASMS. Section 4 introduces two optimization methods, namely the bi-level iteration optimization and two-stage optimization methods based on the surrogate function for fleet allocation on distributed platforms for the DP-ASMS. Section 5 presents a combat and training mission case study involving static and dynamic uncertainty disturbances. Section 6 provides managerial insights into the research area of this study and the resulting performance. Finally, the conclusions of this study are summarized, and future research directions are discussed in Section 7.

2. Problem statement

2.1. Sortie flight planning

2.1.1. Continuous cyclic sortie operation rules

Aircraft wave sortie and recovery operations can be categorized into two modes: wavy and continuous launch operations. In the wavy launch operation mode, wave sortie and recovery are conducted based on the flight cycle (takeoff and landing). Adjacent flight cycles do not overlap, and a preparation cycle (deck operation) exists between them. The continuous launch mode, on the other hand, involves a continuous flight cycle with a staggered overlap between adjacent flight cycles. Maritime operations are typically performed in a single-cycle dual-wave cycle formation in the continuous launch operation mode. This is known as single-cycle double-formation continuous sorties. In this mode, two formations from the available carrier-based aircraft on the platform are alternately selected, sorted, and recovered based on the wave sequence. The cycle is then reiterated until the number of continuous cyclic sorties is achieved. The two formations are released, and the other two formations are re-selected to continue the cycle to achieve a continuous operation. For example, the first formation of aircraft can be launched in the first, third, and fifth waves, while the second formation of aircraft can be launched in the second, fourth, and sixth waves. The entire process is cyclic and regular. The single-cycle double-formation continuous sortie mode can be flexibly formulated based on the deck operation, the number of continuous cyclic sorties, the number of

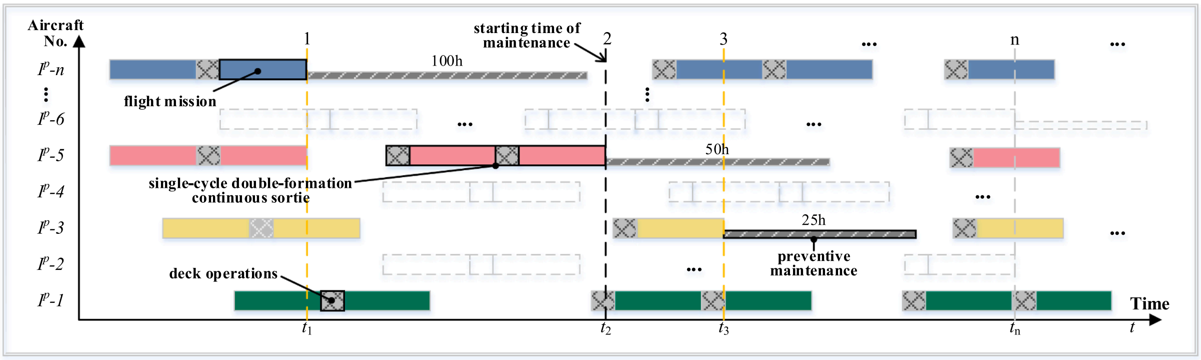


Fig. 2. Schematic illustration showing flight planning of platform.

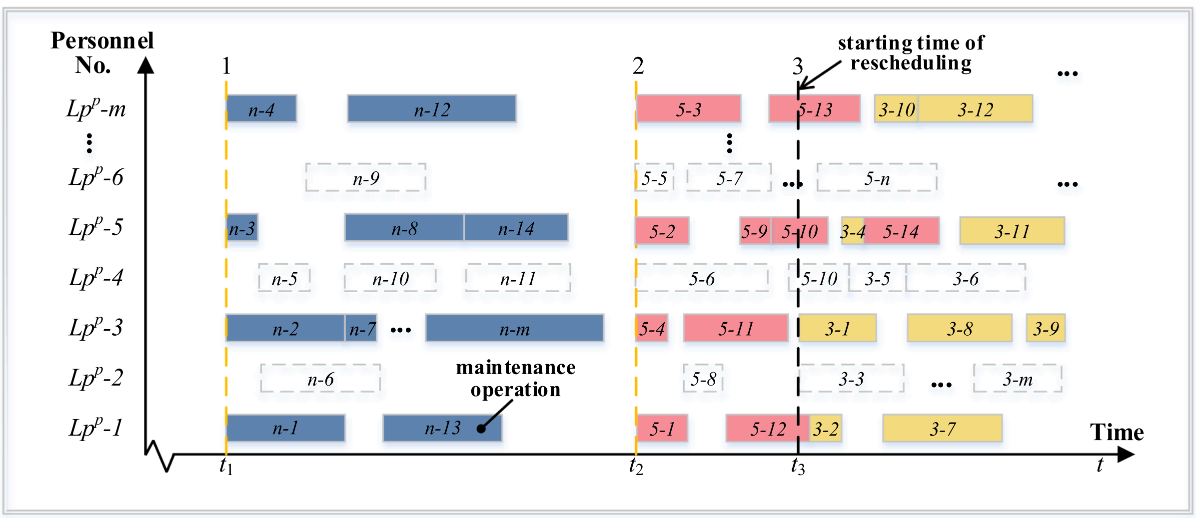


Fig. 3. Schematic illustration showing maintenance and repair scheduling scheme of operations and personnel.

aircraft for every wave sortie, and the total number of waves. A schematic illustration of a single-cycle double-formation continuous sortie is shown in Fig. 1.

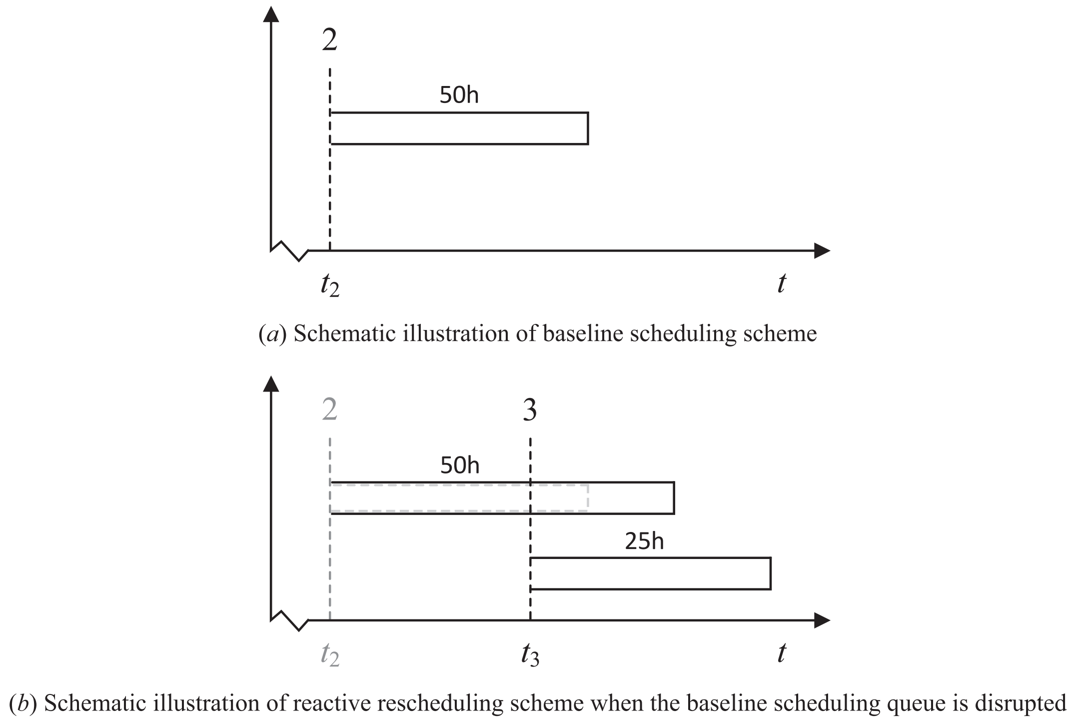
Deck operations are a series of support activities carried out after an aircraft has landed and taxied to the service locations following a mission. These activities include oil and water filling, nitrogen and electricity charging, as well as weapon and ammunition loading. The main purpose of deck operations is to prepare the aircraft for another mission and ensure the safety of aviation operations and systems. During the deck operation cycles, support preparation activities are performed. The duration of deck operations is time-critical and adheres to specific operating durations, such as 1 + 30 (1 h and 30 min) and 2 + 00.

2.1.2. Flight planning

Fleet flight planning involves meeting several mission constraints like the basic desk cycle, continuous cyclic sortie operation rules, and flight duration for each wave. ADMACS is used to determine the status of each aircraft. At the beginning of each wave, the required number of carrier aircraft for the mission is selected from the available fleet, and platform sortie flight planning is established, as shown in Fig. 2. The flight planning contains information like wave sortie planning that involves the number of aircraft performing the mission, deck operations, maintenance mode, and maintenance starting and ending times. Scheduling maintenance time in a hangar bay is a complex task. It involves selecting an aircraft fleet for each wave of flight planning, which affects the preventive maintenance timing of each aircraft. However, entering the maintenance sequence when the number of ongoing tasks is unknown can disrupt the current maintenance scheduling scheme (baseline scheme). Hence, reactive rescheduling is necessary to adjust the baseline scheme (as shown in t_3 in Fig. 2). Meanwhile, the baseline scheduling scheme may also need to be re-adjusted owing to the flight plan, which causes a new aircraft to undergo maintenance. Furthermore, the maintenance duration of each aircraft is uncertain and difficult to predict in advance due to its dynamic nature. Therefore, the final scheduling scheme must be derived from the actual maintenance dynamic scheduling and returned to the ADMACS to refresh the available fleet, which then affects the fleet selection of the wave-flight planning mission. Since wave sortie flight planning and maintenance scheduling are intertwined, an integrated scheduling optimization is necessary.

2.2. Maintenance and repair tasks of carrier-based aircraft

Maintenance and repair tasks for carrier-based aircraft are carried out in the hangar bay of a naval platform. Maintenance involves scheduled preventive maintenance on the aircraft, which is typically done after 25, 50, and 100 flight hours, as well as seven days, three months, six months, or other periodic inspections. Repair, on the other hand, involves fixing any faults that occur, which means repairing the damage to restore the original function and usability of the aircraft to a certain extent [53,54]. In the hangar bay, scheduled aircraft maintenance, troubleshooting of airborne equipment, repairing of airframe structural damage, and maintenance of the aircraft engine are performed. These measures can help maintain and restore the technical condition of the aircraft and ensure that it is mission-ready, thereby



(*b*) Schematic illustration of reactive rescheduling scheme when the baseline scheduling queue is disrupted

Fig. 4. Schematic illustration of reactive scheduling.

maintaining the high availability and allowing the fleet to be readily available for combat and training missions.

The fault repair task of an aircraft involves processes that exhibit serial precedence relations and can be classified into three aspects: fault location, fault repair, and re-inspection. For the preventive maintenance tasks of aircraft, the processes are networked in precedence relations because the immediately preceding operations may not be unique. The activity in the node (AoN) network can be used to represent the networked precedence relations between operations.

Planning for maintenance and repair involves scheduling operations and allocating resources such as personnel and equipment. Maintenance personnel are typically selected based on their professional categories. In the hangar bay, each task is assigned to qualified personnel based on their professional category. When an aircraft needs preventive maintenance, a scheduling scheme of the operations and personnel that meet the model constraints should be established, as depicted in Fig. 3.

Additionally, because some tasks may interfere with the baseline scheduling scheme when the queue is disrupted, the reactive rescheduling scenario mentioned in the previous section must be considered. As shown at t_3 in Fig. 2, Fig. 3, Fig. 4, a 25 flight-hour maintenance task enters the queue. It affects the scheduling of operations which have not yet been scheduled in the 50 flight-hour maintenance task and extends the 50 flight-hour maintenance task makespan. Initially, the operations are divided into three categories: completed, in progress, and not yet scheduled, based on the baseline scheme before the disruption. Then, the status of occupied resources is set, and the baseline scheduling scheme is maintained for completed and in-progress operations. Finally, the operations that have not yet been scheduled (including newly added ones) are rescheduled based on the resource constraints, following the "first-come, first-served" rule.

2.3. Fleet allocation and cross-platform linkage mechanism

The DP-ASMS problem involves two aspects of allocation: platform allocation for the fleet and cross-platform allocation of maintenance tasks during missions. The number of aircraft supported on distributed platforms is taken into consideration as a constraint. The platform allocation for the fleet involves assigning carrier-based aircraft to each platform based on their accumulated flight hours. When an aircraft reaches a specific moment, such as 25, 50, or 100 flight hours, it is transferred to the platform hangar bay for scheduled preventive maintenance. The accumulated flight hours of an aircraft determine its scheduled maintenance timing and indirectly affect the available fleet for subsequent missions, i.e., the establishment of sortie flight planning. Therefore, platform allocation is a crucial factor in flight planning as it directly affects the effectiveness of the subsequent sortie-flight planning phase and the completion of combat and training missions.

During a flight mission, an aircraft that suffers from a random fault or battle damage is transported to the hangar bay platform for repair after the recovery phase. If there are many faulty aircraft during an intense battle situation, they may all be docked in the platform, which could cause a backlog of tasks in the hangar bay. This could result in decreased fleet availability over time, slow recovery, and adversely affect the ability to generate subsequent combat power. To avoid such a scenario, a cross-platform linkage mechanism based on heuristic rules for the task allocation of distributed repair was proposed under the concept of distributed maritime operations.

The distributed system of assertive heterogeneous network fusion communication was used to achieve accurate real-time data sharing of distributed platforms to achieve the "platform–aircraft–platform linkage." An aircraft with a fault or battle damage during the flight mission receives the load status data from the mother platform and the hangar bay of other platforms prior to the wave recovery phase. Subsequently, the aircraft comprehensively assesses the recovery platform based on the heuristic rules of task allocation for distributed repair.

If the assessment result of the maintenance task is transferred to other platforms for repair, the faulty aircraft is added to the target platform recovery formation during the recovery phase for cross-platform recovery. This helps disperse the load pressure on the platform maintenance. Moreover, the corresponding number of aircraft in good condition that has not yet been recovered are selected from the target platform and transferred to the mother platform of the faulty aircraft for recovery such that the loss difference can be replenished. A schematic illustration of the repair task based on cross-platform transfer

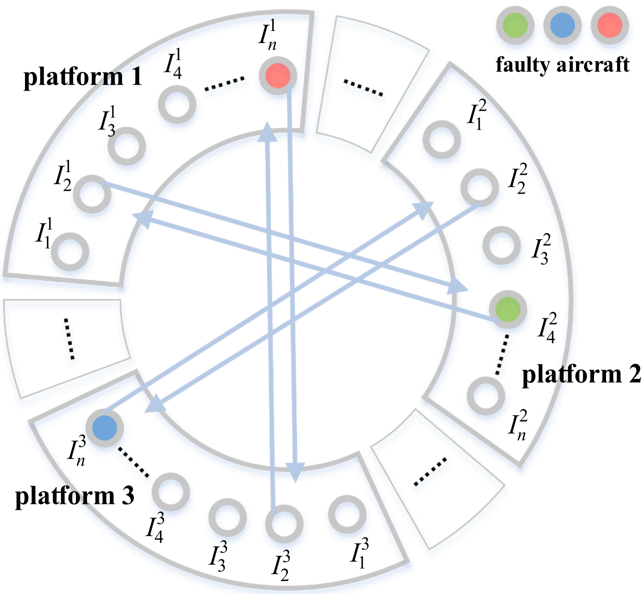


Fig. 5. Schematic illustration of repair task based on cross-platform transfer.

is shown in Fig. 5.

As described above, the DP-ASMS sequentially integrates platform allocation for the fleet, sortie flight planning, cross-platform aircraft repair task allocation, and aircraft maintenance and repair tasks to form a complete problem system. The research content and framework of this study are illustrated in Fig. 6.

2.4. Methodology

Optimizing the scheduling of fleet wave sorties and maintenance for naval distributed platforms is a complex task. The DP-ASMS involves optimizing the fleet allocation of the overall platform as well as sortie flight planning and maintenance scheduling for each sub-platform on the distributed platform. The optimization is divided into two hierarchical levels, comprising of upper-level modules for the overall platform and lower-level modules for sub-platforms. At the onset of optimization, two steps are taken. Initially, we seek a feasible but not optimal solution for the overall platform and then explore and store multiple compromise solutions for the sub-platforms. Subsequently, after local optimizations of multiple sub-platforms, it is necessary to reallocate the fleet allocation of the overall platform. The approach to solving this problem is synthesizing a bi-level iteration system [55]. Bi-level programming comprises of separate upper and lower optimization tasks. In the upper optimization task, a solution must fulfill its own constraints while also being the optimal solution for another optimization problem, known as the lower optimization problem. Although the concept may seem intricate, bi-level programming is frequently used in practical optimization scenarios. When a solution in the upper-level optimization task needs to be acceptable physically or functionally, bi-level solutions arise. These may take different forms, such as stable solutions, solutions in equilibrium, or solutions that adhere to specific conservation principles. These conditions can be used as a lower-level optimization task. This leads to an iterative optimization process between the two levels, with the goal of achieving global optimality. However, this process can result in complex interactions between the levels.

However, the high computational costs involved mean that bi-level planning is often not used to address these issues in practice. Optimizing bi-level programming is a complex and demanding task because of its nested nature. It is, in fact, a well-known NP-hard problem [56], and checking the local optimality of a solution is also NP-hard [57]. This is due to the lower-level optimizer being called by each upper-level assessment, resulting in significant computational costs. Lower-level optimization problems typically exhibit a multi-modal, ill-conditioned, or deceptive nature, posing a challenge to optimizing the lower-level problem itself. In the discipline of mathematical optimization, bi-level programming problems are frequently transformed into two-stage optimization problems [10,58]. Employing some approximate methods to replace the upper-level or lower-level problems may be appropriate. The optimization process begins at the upper level and employs certain approximations to allocate the optimization results to lower-level modules. The lower-level modules maintain their original optimization processes, ensuring their final objective values closely approximate the specified values at the level of the bi-level planning problem [59]. In certain cases, it may be necessary to compare results between two methods due to the absence of approximate solutions or

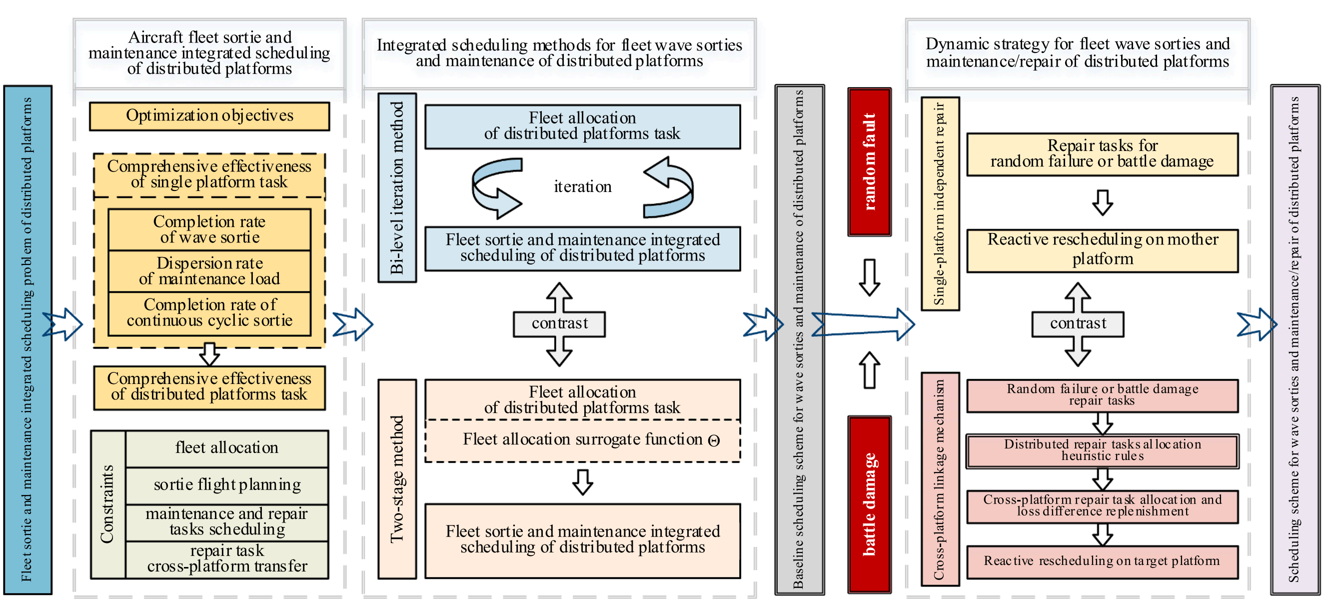


Fig. 6. Research content and framework.

Table 2
Notations and description for static DP-ASMS mathematical modeling.

Notations	Descriptions
I	The set of carrier-based aircraft to be allocated, i.e., $I = \{1,2,\cdots,\mathrm{Ni}\}$, where Ni is the number of carrier-based aircraft to be allocated.
I^p	The set of carrier-based aircraft on the pth platform, i.e., $I = \{1,2,\cdots,\mathrm{Ni}^p\}$, where Ni^p is the number of carrier aircraft on the pth platform.
P	The set of maritime platforms, i.e., $P = \{1,2,\cdots,\mathrm{Np}\}$, where Np is the number of platforms.
W^p	The set of sortie waves on the pth platform, i.e., $W^p = \{1,2,\cdots,\mathrm{Nw}^p\}$, where Nw^p is the number of sortie waves.
n	The set of maintenance or repair times of the ith carrier-based aircraft on the pth platform, i.e., $n = \{1,2,\cdots,\mathrm{Nn}_i^p\}$.
Ta_{in}^p	The available flight hours before performing the nth scheduled maintenance or repair on the ith carrier-based aircraft on the pth platform.
Tr_{in}^p	The theoretical maintenance duration for the nth scheduled maintenance or repair of the ith carrier-based aircraft on the pth platform.
Tl	The offset timing of maintenance, which offers flexibility in the timing of maintenance within an allowable offset ($\pm$Tl).
Tw^p	The flight mission duration on the pth platform.
Td^p	The deck cycle duration on the pth platform.
To^p	The deck operation duration on the pth platform.
Nc^p	The number of continuous cyclic sorties on the pth platform.
Ng^p	The number of formations of cyclic sorties on the pth platform.
Nd^p	The number of carrier-based aircraft required for the wave sortie on the pth platform.
Rt^p	The set of maintenance and repair starting times on the pth platform.
Ia_t^p	The set of available aircraft at time t on the pth platform, i.e., $\mathrm{Ia}_t^p = \{1,2,\cdots,\mathrm{Na}_t^p\}$, where Na_t^p is the number of available aircraft at time t on the pth platform.
Io_t^p	The set of carrier-based aircraft to be repaired and undergo maintenance at moment t on the pth platform.
Ir_t^p	The set of carrier-based aircraft to be repaired at moment t on the pth platform, i.e., $\mathrm{Ir}_t^p = \{1,2,\cdots,\mathrm{Nr}_t^p\}$, where Nr_t^p is the number of aircraft to be repaired at moment t on the pth platform.
Ns_t^p	The number of carrier-based aircraft to be repaired via the task allocation of distributed repair at moment t on the pth platform.
Im_t^p	The set of aircraft to undergo maintenance at moment t on the pth platform.
J_{in}^p	The set of maintenance and repair operations for the nth scheduled maintenance or repair of the ith carrier-based aircraft on the pth platform, $J_{in}^p = \{1,2,\cdots,\lvert J_{in}^p\rvert\}$.
J	The set of maintenance and repair operations of a fleet, i.e., $J = \{(i,j)\mid i\in I, j\in J_{in}^p\}$.
A_t^p	The set of maintenance and repair operations in progress at time t on the pth platform.
A_{it}^p	The set of maintenance and repair operations in progress of the ith carrier-based aircraft at time t on the pth platform.
T_{in}^p	The makespan for the nth scheduled maintenance or repair of the ith carrier-based aircraft on the pth platform.
Ps_{inj}^p	The immediate predecessors set of operations (i,j) for the nth scheduled maintenance or repair on the pth platform.
d_{ij}	The maintenance duration of operation (i,j) on the pth platform.
BM	Sufficiently large real numbers.
Kc	The set of skill categories for maintenance personnel, i.e., $\mathrm{Kc} = \{1,2,\cdots,\lvert\mathrm{Kc}\rvert\}$.
Lp_k^p	The set of maintenance personnel with the kth category skill on the pth platform.
rc_{injk}^p	The demand for the kth category skill of operation (i,j) for the nth scheduled maintenance or repair on the pth platform.
Sm_{inj}^p	A decision variable indicating the starting time of operation (i,j) for the nth scheduled maintenance or repair on the pth platform.
Em_{inj}^p	A decision variable indicating the ending time of operation (i,j) for the nth scheduled maintenance or repair on the pth platform.
Xa_{ip}	A decision variable of value 0 or 1, where 1 indicates that the ith carrier-based aircraft is allocated to the pth platform, whereas 0 indicates otherwise.
Xb_{iw}^p	A decision variable of value 0 or 1, where 1 indicates that the ith carrier-based aircraft that participated in the wth wave flight mission, whereas 0 indicates otherwise.
Yb_{iw}^p	A decision variable of value 0 or 1, where 1 indicates that the ith carrier-based aircraft on the pth platform that underwent scheduled maintenance in the wth wave flight mission, whereas 0 indicates that the ith carrier-based aircraft on the pth platform resides on the platform in the wth wave flight mission.
Xp_{injkl}^p	A decision variable of value 0 or 1, where 1 indicates that the operation (i,j) is allocated to the lth maintenance personnel who uses the kth category skill for the nth scheduled maintenance or repair on the pth platform, whereas 0 indicates otherwise.
Yp_{ijeg}^p	A decision variable of value 0 or 1, where 1 indicates that the operation (i,j) is allocated to the same maintenance personnel as operation (e,g) on the pth platform, and that (i,j) is prioritized over (e,g), whereas 0 indicates otherwise.

unacceptable practical accuracy. While bi-level programming can be used to pose and resolve problems related to ensuring physically or functionally feasible solutions, computational costs, efficiency, and precision often lead researchers to seek some form of approximation in order to streamline computations [10,58]. For instance, this simplification concept will be utilized by the two-stage optimization method to be discussed later.

3. Mathematical formulation for DP-ASMS

3.1. Modeling assumptions

The modeling assumptions introduced were as follows:

1) The relevant parameters of the sortie flight mission are known.
2) The costs of the repair task based on cross-platform transfer are not considered.
3) The task allocation and transfer time of the platform and hangar bay are not considered.
4) Maintenance and repair operations cannot be interrupted after they commence.
5) Each platform can guarantee all modes of repair tasks for all aircraft.

3.2. Notations

The modeling notations used in static DP-ASMS are shown in Table 2.

3.3. Optimization objectives of DP-ASMS

1) Comprehensive effectiveness of distributed platform task

The combat system is formed jointly by multiple platforms in maritime-distributed combat and training missions. The platforms collaborate with each other, and the tasks are completed via labor division. Based on the comprehensive effectiveness of a single-platform task as support, the comprehensive optimization objective F of the DP-ASMS is constructed as follows:

$$\max F = \sum_{p\in P} v^p \cdot f^p \tag{1}$$

where f^p indicates the effectiveness evaluation of platform p, and v^p denotes the impact weight of each platform. The decision maker can determine the weight based on the task and platform.

2) Comprehensive effectiveness of single platform

The comprehensive effectiveness optimization target f^p of a single platform is expressed as follows:

$$\max f^p = \gamma_1 \cdot \mathrm{WR}^p + \gamma_2 \cdot \mathrm{MR}^p + \gamma_3 \cdot \mathrm{CR}^p, \forall p \in P, \tag{2}$$

Meanwhile, the comprehensive effectiveness of a single platform task is reflected in the following three aspects:

i. Completion rate of the wave sortie, WR

The carrier-based aircraft on a platform will reach the scheduled maintenance moment or fault after executing a mission; therefore, some available aircraft will not satisfy the requirement for the number of aircraft for wave sorties. At this time, the wave sortie is known as the missing wave. In contrast to the number of complete waves that significantly affect the combat and training mission, the completion rate of the wave sortie is expressed as follows:

$$\max \mathrm{WR}^p = \frac{\sum_{w\in W^p}\mathrm{Yc}^p_w}{\mathrm{Nw}^p}, \forall p \in P, \tag{3}$$

where Yc^p_w defines the mission completion status of the wave sortie variable when $\sum_{i\in I^p}\mathrm{Xb}^p_{iw} = \mathrm{Nd}^p, \forall p \in P, \forall w \in W^p$. Here, $\mathrm{Yc}^p_w = 1$ implies that the wth wave completed a mission, whereas $\mathrm{Yc}^p_w = 0$ implies that the wth wave did not complete a mission. The higher the WR, the better is the flight planning optimization effect.

ii. Dispersion rate of maintenance load, MR

The reasonable allocation of the mission sequence to each aircraft, maintenance timing dispersion of each aircraft, and formation of a ladder use interval can avoid a reduction in the number of available aircraft caused by the concentration of maintenance load in the platform hangar bay, which affects the execution of combat and training missions.

We define an index for the dispersion rate of the maintenance load and calculate the distribution standard deviation of the maintenance time of aircraft on each platform. The calculation formula is as follows:

$$\max \mathrm{MR}^p = \mathrm{std}(\mathrm{Rt}^p), \tag{4}$$

where $\mathrm{std}(\cdot)$ is the standard deviation calculation function; the higher the Rt^p, the greater is the maintenance timing dispersion of the pth platform aircraft, and the better is the flight planning optimization effect.

iii. Completion rate of continuous cyclic sortie, CR

In the continuous launch operation mode, the fleet on a platform can be categorized into several formations that are sorted and recovered alternately based on the wave sequence. To consider the continuity of the pilot's sortie mission, the same aircraft must be flown in several consecutive waves to maintain the piloting habit. This avoids incurring a cost for accessing the hangar bay and performing deck transfers, which are required in the frequent replacement of sortied aircraft. Continuous cyclic sortie planning is the basis for maintaining efficiency and is vital to the operational effectiveness of the fleet. An evaluation index is defined to satisfy the CR, and it is expressed as follows:

$$\max \mathrm{CR}^p = \frac{\sum_{i\in I^p}\sum_{w\in W^p}\mathrm{Yd}^p_w}{\frac{\mathrm{Nd}^p\cdot \mathrm{Nw}^p}{\mathrm{Nc}^p}}, \forall p \in P, \tag{5}$$

where Yd^p_w is the variable of the continuous cyclic sortie when $\sum_{e=w}^{w+\mathrm{Ng}^p\cdot\mathrm{Nc}^p-1}\mathrm{Xb}^p_{ie} = \mathrm{Nc}^p, \forall p \in P, \forall i \in I^p, \forall w \in W^p, \forall (w+\mathrm{Ng}^p\cdot\mathrm{Nc}^p-1) \in W^p$. $\mathrm{Yd}^p_{iw} = 1$ implies that the ith aircraft completes a continuous cyclic within the wave interval $[w, w+\mathrm{Ng}^p\cdot\mathrm{Nc}^p-1]$, whereas $\mathrm{Yd}^p_{iw} = 0$ implies otherwise. The greater the CR, the better is the optimization effect of the sortie flight planning.

In the actual fleet wave sortie and maintenance integrated scheduling planning, the three effectiveness indicators above have certain priority levels. γ_1, γ_2, and γ_3 are the impact weights of the effectiveness evaluation indicator, and the decision maker can assign their values based on their importance.

3.4. Constraints of DP-ASMS

1) Constraints of fleet allocation on distributed platforms

The number of carrier-based aircraft allocated to a platform is equal to the number of aircraft that the platform must contain. Furthermore, each aircraft can be allocated to only one platform in the same allocation, and the following constraints are formulated:

$$\sum_{i\in I}\mathrm{Xa}_{ip} = \mathrm{Ni}^p, \forall p \in P \tag{6}$$

$$\sum_{p\in P}\mathrm{Xa}_{ip} = 1, \forall i \in I \tag{7}$$

2) Constraints of sortie flight planning

A continuous cyclic sortie requires the imposition of constraints pertaining to aircraft selection in adjacent wave formations: Each aircraft must be mutually exclusive when selecting sorties in adjacent waves. The range of mutual exclusion is associated with the formation number of cyclic sorties Ng^p. If $\mathrm{Ng}^p = 3$, $w = 1$, then the $\mathrm{Xb}^p_{i,*}$ in first wave is mutually exclusive with the second and third waves (the value cannot be taken as 1 at the same time). Additionally, a mutual exclusion constraint is imposed for aircraft flight missions and the timing of scheduled maintenance/residing on the platform. The constraint is written as

$$\mathrm{Xb}^p_{iw}\cdot\mathrm{Xb}^p_{iw'} = 0, \forall p \in P, \forall i \in I^p, \forall w \in W^p, \forall w' \in [w+1, w+\mathrm{Ng}^p-1] \subseteq W^p \tag{8}$$

$$\mathrm{Xb}^p_{iw}\cdot\mathrm{Yb}^p_{iw} = 0, \forall p \in P, \forall i \in I^p, \forall w \in W^p \tag{9}$$

A quantity constraint is imposed for each flight sortie wave mission for the aircraft, as follows:

$$\sum_{i\in I^p}\mathrm{Xb}^p_{iw}\begin{cases} = \mathrm{Nd}^p\ ,\ \mathrm{Nd}^p \leqslant \mathrm{Ni}^p - \sum_{i\in I^p}\mathrm{Xb}^p_{i,w-1} - \sum_{i\in I^p}\mathrm{Yb}^p_{iw} \\ < \mathrm{Nd}^p\ ,\ \text{else}\end{cases}, \forall p \in P, \forall w \in W^p, \tag{10}$$

where $\sum_{i\in I^p}\mathrm{Xb}^p_{i,w-1}$ indicates the number of aircraft occupied by the pth platform for the $(w-1)$th wave mission, Q the number of aircraft undergoing scheduled maintenance on the pth platform for the wth wave, and $\mathrm{Ni}^p - \sum_{i\in I^p}\mathrm{Xb}^p_{i,w-1} - \sum_{i\in I^p}\mathrm{Yb}^p_{iw}$ the number of available aircraft on the pth platform for the wth wave.

A constraint is imposed on the scheduled maintenance timing of carrier-based aircraft, which causes the ith aircraft on the pth platform to have fewer available flight hours before undergoing the nth scheduled maintenance after the mission is performed. This constraint offers flexibility in the scheduled maintenance timing within the allowable offset ($\pm$Tl) before and after the approaching overhaul moment. The constraint is formulated as follows:

$$-\mathrm{Tl} \leqslant \left(\mathrm{Ta}^p_{in} - \mathrm{Tw}^p\cdot\sum_{w=1}^{e}\mathrm{Xb}^p_{iw}\right)\cdot\mathrm{Yb}^p_{i,e+1} \leqslant \mathrm{Tl}, \forall p \in P, \forall i \in I^p, \forall e \in W^p \tag{11}$$

Additionally, a constraint associated with sortie flight planning and maintenance scheduling is imposed: the ith aircraft on the pth platform entering scheduled maintenance/residing on the platform coincides with the wave span for performing the nth scheduled maintenance.

$$\sum_{w=1}^{e}\mathrm{Yb}^p_{iw} = \lfloor\frac{\mathrm{Em}^p_{in|J^p_{in}|}}{\mathrm{Td}^p}\rfloor - \lceil\frac{\mathrm{Sm}^p_{in1}}{\mathrm{Td}^p}\rceil, \forall p \in P, \forall i \in I^p, \forall e \in W^p \tag{12}$$

3) Constraints of maintenance and repair task scheduling

Table 3
Decision variables used in static DP-ASMS mathematical modeling and their descriptions.

Notations	Descriptions
Xc_{timn}	A decision variable of value 0 or 1, where 1 indicates that the *ith* $(i \in \mathrm{Ir}_t^m)$ aircraft is transferred from platform *m* to platform *n* for repair at moment *t*, whereas 0 indicates otherwise.
Xd_{tinm}	A decision variable of value 0 or 1, where 1 indicates that the *ith* $(i \in \mathrm{Ia}_t^n)$ aircraft is transferred from platform *n* to platform *m* to compensate for the difference at moment *t*, whereas 0 indicates otherwise.

Maintenance is performed sequentially based on the established precedence relations, and subsequent operations must begin immediately after the preceding operation is completed. The constraint is written as follows:

$$\mathrm{Sm}_{inj}^{p} \geqslant \mathrm{Em}_{inh}^{p}, \forall p \in P, \forall i \in I^{p}, \forall (i,h) \in \mathrm{Ps}_{inj}^{p}, j > h, \forall (i,j) \in J \tag{13}$$

The starting and ending time constraints of the maintenance operation are as follows:

$$\mathrm{Em}_{inj}^{p} = \mathrm{Sm}_{inj}^{p} + d_{ij}, \forall i \in \mathrm{Io}_{t}^{p}, \forall j \in J_i \tag{14}$$

The number of skills required for a maintenance operation should be equal to the number of maintenance personnel allocated to the operation based on those skills. In this regard, the following constraints are formulated:

$$\sum_{l \in \mathrm{Lp}_k^p} \mathrm{Xp}_{injkl}^{p} = \mathrm{rc}_{injk}, \forall p \in P, \forall (i,j) \in J, \forall k \in \mathrm{Kc} \tag{15}$$

The number of skills possessed by the maintenance personnel to perform the maintenance tasks for each operation is formulated as follows:

$$\sum_{k \in \mathrm{Kc}} \mathrm{Xp}_{injkl}^{p} \leqslant 1, \forall p \in P, \forall (i,j) \in J, \forall l \in \mathrm{Lp}_k^p \tag{16}$$

When different operations require the same maintenance personnel, the order of operations must be established based on precedence relations. The constraints for conflicting maintenance personnel are formulated as follows:

$$\mathrm{Sm}_{inj}^{p} + d_{ij} \leqslant \mathrm{Sm}_{eng}^{p} + \mathrm{BM}\cdot\left(1 - \mathrm{Yp}_{ijeg}^{p}\right), \forall p \in P, \forall (i,j),(e,g) \in J \tag{17}$$

By combining these constraints, the static modeling of the DP-ASMS can be performed based on the equations shown in Eq. (18).

$$\begin{cases} \max F = \sum_{p \in P} v^{p} \cdot f^{p} \\ \max f^{p} = \gamma_1 \cdot \mathrm{WR}^{p} + \gamma_2 \cdot \mathrm{MR}^{p} + \gamma_3 \cdot \mathrm{CR}^{p} \\ \text{s.t.} \ \ \mathrm{Constraints}(6) \sim (17) \end{cases} \tag{18}$$

Dynamic repair tasks of random faults or battle damage are incorporated into the static modeling to construct a dynamic scheduling model of the DP-ASMS. Subsequently, the decision variables listed in Table 3 are added.

4) Constraints of repair task based on cross-platform transfer

A constraint for the repair task based on cross-platform transfer is added to the model expressed in Eq. (18). The constraint specifies that the number of repair tasks to be transferred must not be greater than the total number of aircraft to be repaired on the platform, expressed as

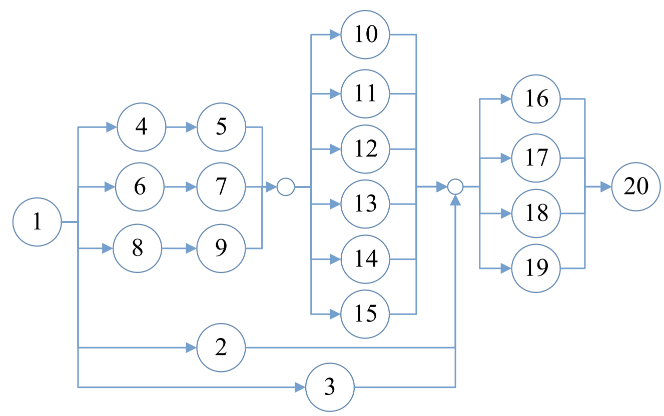


Fig. 8. AoN network for single carrier-based aircraft.

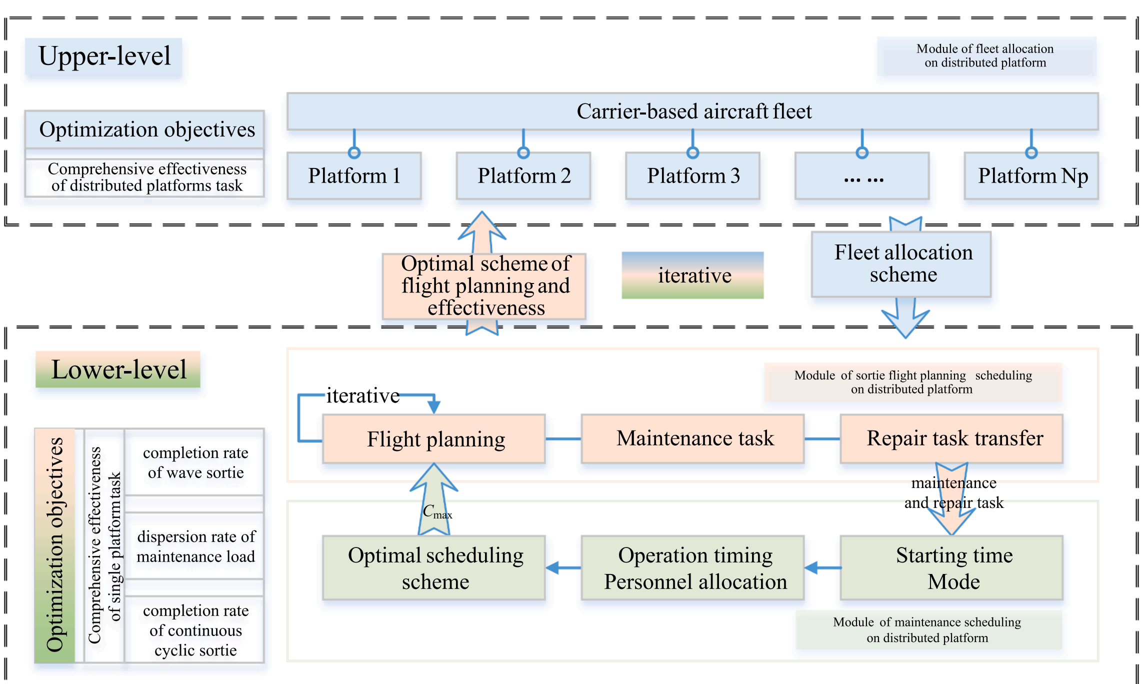
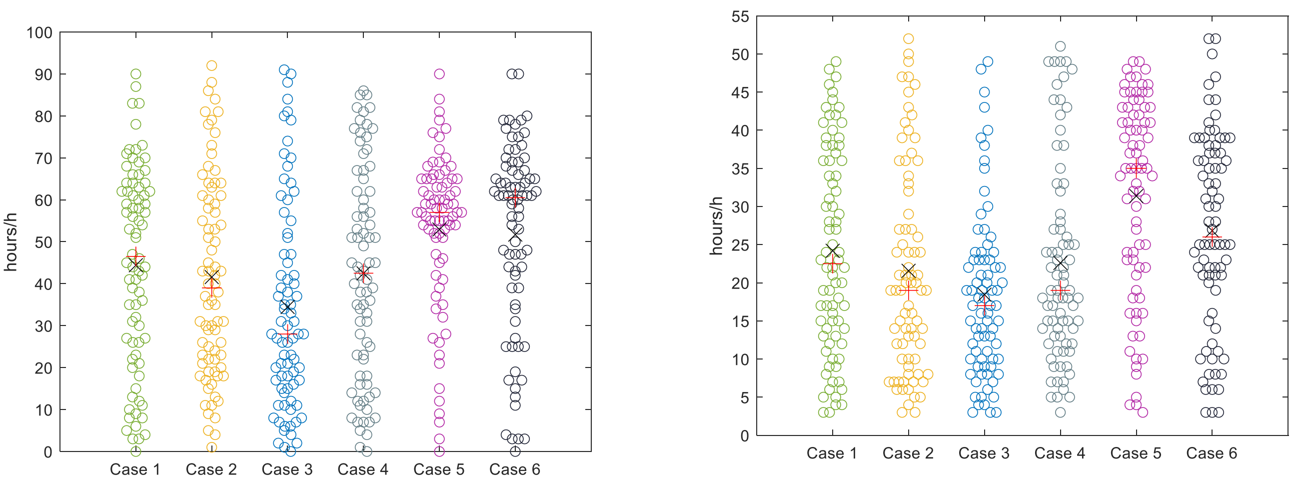


Fig. 7. Bi-level optimization scheduling framework.

Table 4
Duration of maintenance and repair operations of carrier-based aircraft.

Modes	Operation No.																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
	Operation duration (min)																			
M1	0	90	150	40	30	40	50	30	40	75	100	75	80	90	65	15	50	40	30	0
M2	0	125	225	40	40	40	60	30	40	150	150	130	130	140	80	40	90	50	50	0
M3	0	170	330	50	60	50	75	50	60	240	200	225	165	220	230	80	130	90	70	0
M4	0	0	0	0	120	0	0	0	0	220	0	0	0	0	0	60	0	0	0	0
M5	0	0	0	0	95	0	0	0	0	265	0	0	0	0	0	110	0	0	0	0
M6	0	0	0	0	130	0	0	0	0	235	0	0	0	0	0	85	0	0	0	0



(*a*) Initial value of accumulated flight hours of each aircraft

(*b*) Initial value of available flight hours before next scheduled maintenance

Fig. 9. Initial value setting of fleet for six groups of cases.

follows:

$$\sum_{i\in \mathrm{Ir}_t^m} \mathrm{Xc}_{timn} \leqslant \mathrm{Nr}_t^p, \forall m,n\in P, m\neq n \tag{19}$$

The total number of transferred aircraft is equal to the total number of replenished aircraft. Therefore, the constraint is written as

$$\sum_{m,n\in P} \mathrm{Xc}_{timn} = \sum_{m,n\in P} \mathrm{Xd}_{ti'nm}, \forall i\in \mathrm{Ir}_t^m, \forall i'\in \mathrm{Ia}_t^n, m\neq n \tag{20}$$

Combining the above, the dynamic modeling of the DP-ASMS can be constructed as follows:

$$\begin{cases} \max F = \sum_{p\in P} v^p \cdot f^p \\ \max f^p = \gamma_1 \cdot \mathrm{WR}^p + \gamma_2 \cdot \mathrm{MR}^p + \gamma_3 \cdot \mathrm{CR}^p \\ \text{s.t. Constraints}(6)\sim(17),(19)\sim(20) \end{cases} \tag{21}$$

4. Optimization methods for DP-ASMS

4.1. Bi-level iteration optimization method

The DP-ASMS can be divided into two modules based on the hierarchy of fleet allocation decisions, wave sorties, and maintenance of naval distributed platforms. The upper-level module deals with fleet allocation on the distributed platform, while the lower-level module focuses on sortie flight planning and maintenance scheduling on the distributed platform. The bi-level framework is optimized through an interactive iterative process of the two modules, thus forming a master–slave recursion hierarchical framework. The upper-level module controls the lower-level decisions, and the lower-level decisions are used as input conditions and combined with their objectives to optimize decision-making. For a feasible upper-level solution, the optimal solution of the lower-level optimization problem must correspond to it. Meanwhile, the lower-level provides feedback and guidance to the upper-level decision, which adjusts its own decision based on the optimal solution of the lower-level. The upper-level decision is then output to the lower-level again for an iterative interaction, which leads to the optimal solution of the upper-level scheduling decision objective. The upper- and lower-levels are independent of each other and have their own decision-optimization goals.

4.1.1. Optimization framework

The bi-level optimization framework is shown in Fig. 7, and the specific steps for executing the algorithm are as follows:

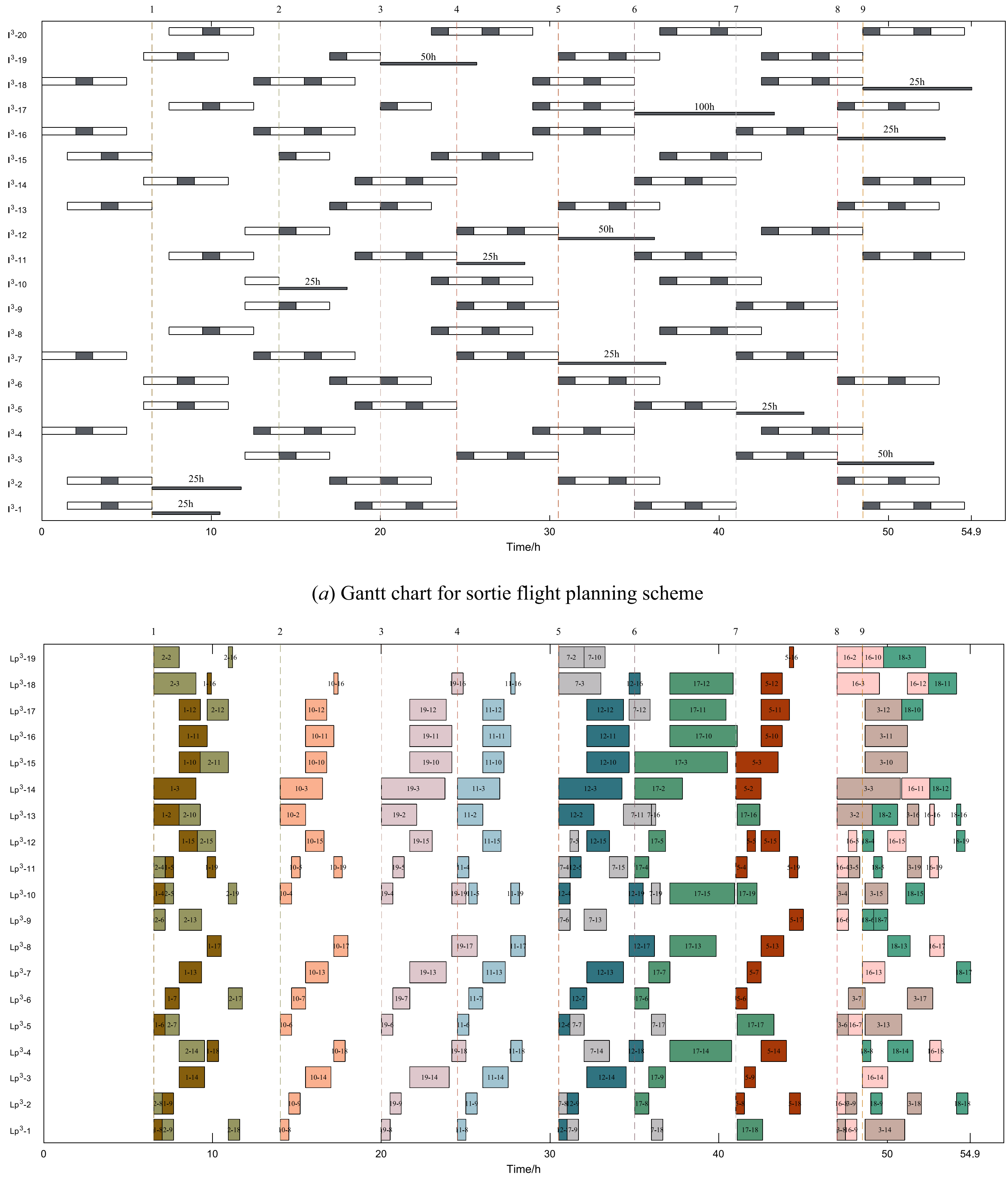
1) Upper-level algorithm

Step 1 Input the flight state attributes of the fleet, initialize the upper-level population and evaluate the fleet allocation on the distributed platform. Subsequently, the allocation results are output to the lower-level algorithm.

Step 2 Input the optimal results of the flight planning and the effectiveness of each platform of the lower-level algorithm. Subsequently, calculate the value of the population objective function of the upper-level algorithm.

Step 3 Execute the operation pertaining to population genetic evolution.

Step 3.1 The population conducts a two-individual tournament selection to choose parents with better fitness, creating a parent population half the size of the whole population.



(*a*) Gantt chart for sortie flight planning scheme

(*b*) Gantt chart for maintenance scheme

Fig. 10. Gantt chart for bi-level optimization scheduling scheme of Case 3 (Platform 3).

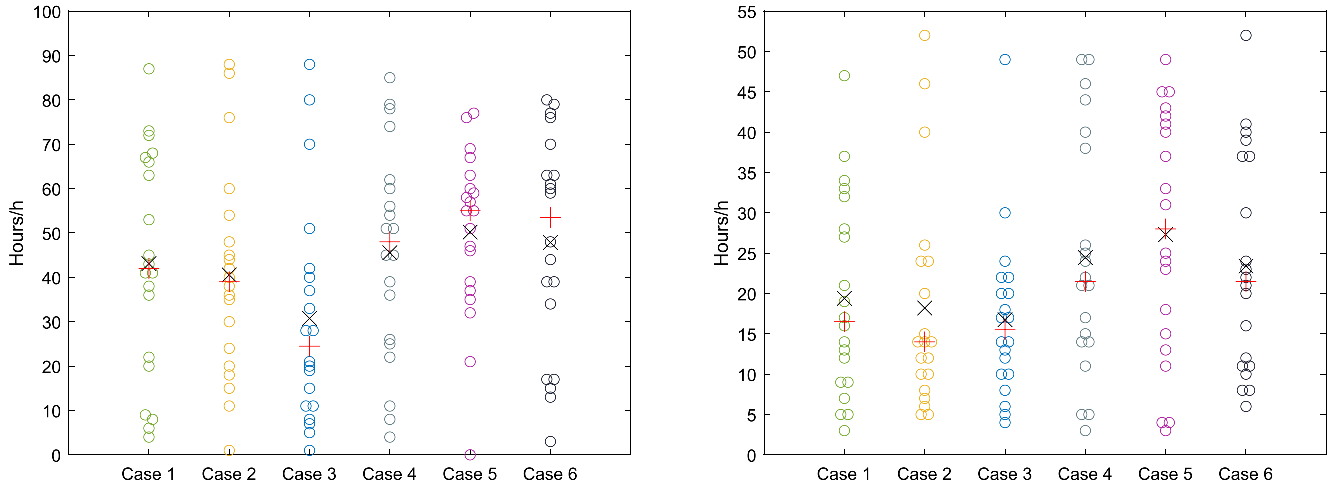
Step 3.2 A two-point crossover operation is performed within the parent population to generate the offspring population.

Step 3.3 The offspring population performs a random key mutation operation.

Step 4 Distribute the platform population allocation, evaluate the operation, and output the allocation results to the lower-level algorithm based on the offspring population.

Step 5 Repeat **Steps 2–4** until the end-of-iteration condition is satisfied.

Step 6 Output the optimal individual allocation result, the optimal



(a) Allocation results of accumulated flight hours of each aircraft

(b) Allocation results of available flight hours before next scheduled maintenance

Fig. 11. Fleet allocation results of Platform 3.

Table 5
Scheduling results obtained using bi-level iterative optimization method.

Cases	Platforms	Optimization objectives				
		F	f	WR	MR	CR
Case 1	Platform 1	0.667	0.678	1	18.509	0.611
	Platform 2		0.672	1	20.216	0.556
	Platform 3		0.635	1	17.074	0.417
Case 2	Platform 1	0.660	0.666	1	18.211	0.556
	Platform 2		0.668	1	18.951	0.556
	Platform 3		0.634	1	13.159	0.472
Case 3	Platform 1	0.655	0.656	1	16.766	0.528
	Platform 2		0.664	1	19.531	0.528
	Platform 3		0.638	1	14.580	0.472
Case 4	Platform 1	0.662	0.659	1	16.120	0.556
	Platform 2		0.663	1	17.279	0.556
	Platform 3		0.667	1	20.319	0.528
Case 5	Platform 1	0.687	0.697	1	19.242	0.694
	Platform 2		0.692	1	23.389	0.611
	Platform 3		0.655	1	20.232	0.472
Case 6	Platform 1	0.678	0.704	1	23.410	0.667
	Platform 2		0.667	1	15.011	0.611
	Platform 3		0.633	1	14.580	0.444

result of flight planning, and the effectiveness of each corresponding platform.

2) Lower-level algorithm

Step 1 Input the upper-level algorithm's distributed-platform fleet allocation results and initialize the lower-level population.

Step 2 Evaluate each individual of the population in **Steps 2–4** and perform the following judgment operations (as stage variables) as time progresses.

Step 2.1 Determine whether the available fleet requires scheduled maintenance. If yes, proceed to **Step 2.1.1**; otherwise, proceed to **Step 2.2** to update the available fleet.

Step 2.1.1 Input the maintenance mode and maintenance start time and determine whether task platform transfer must be performed based on the heuristic rules of task allocation for distributed repair.

Step 2.1.2 Allocate tasks for distributed repair.

Step 2.1.3 Determine whether reactive rescheduling should be performed. If yes, proceed to **Step 2.1.4**; otherwise, proceed to **Step 2.1.5**.

Step 2.1.4 Input the maintenance baseline scheduling results.

Step 2.1.5 Initialize the maintenance task priority encoded based on the "first-come, first-served" rule.

Step 2.1.6 Perform reactive rescheduling and allocate maintenance personnel based on constraints and load-balancing principles. Subsequently, perform maintenance tasks to evaluate the operations.

Step 2.1.7 Save the maintenance baseline scheduling results and output the maintenance completion time ($C_{\max}$) for each aircraft.

Step 2.2 Determine whether the wave and maintenance missions are completed, and update the available fleet.

Step 2.3 Perform wave sortie aircraft selection under the flight planning constraints.

Step 3 Repeat **Step 2** until all wave missions are completed.

Step 4 Calculate the objective function value of the individual generation scheme.

Step 5 Perform the operation pertaining to population genetic evolution.

Step 5.1 The population performs a two-individual tournament selection operation to select individuals with better fitness as parent individuals to generate a population one-half the size the parent population.

Step 5.2 A two-point crossover operation is performed in the parent population to generate the offspring population.

Step 5.3 A random key mutation operation is performed on the offspring population.

Step 6 Repeat **Steps 2–5** until the end-of-iteration condition is satisfied.

Step 7 Output the optimal results of the flight planning and the effectiveness of each platform of the lower-level algorithm to the upper-level algorithm.

4.1.2. Encoding and evaluation

The algorithm uses random key encoding in the interval $[0, 1]$ to prevent it from generating schemes that do not satisfy the allocation and flight planning constraints in subsequent crossover and mutation operations. The upper-level encoding corresponds to the allocation priority number of each aircraft, i.e., $x_L = [S_1, S_2, \cdots, S_{Ni}]$, based on the priority number allocated to the aircraft on the platform, from the smallest to the

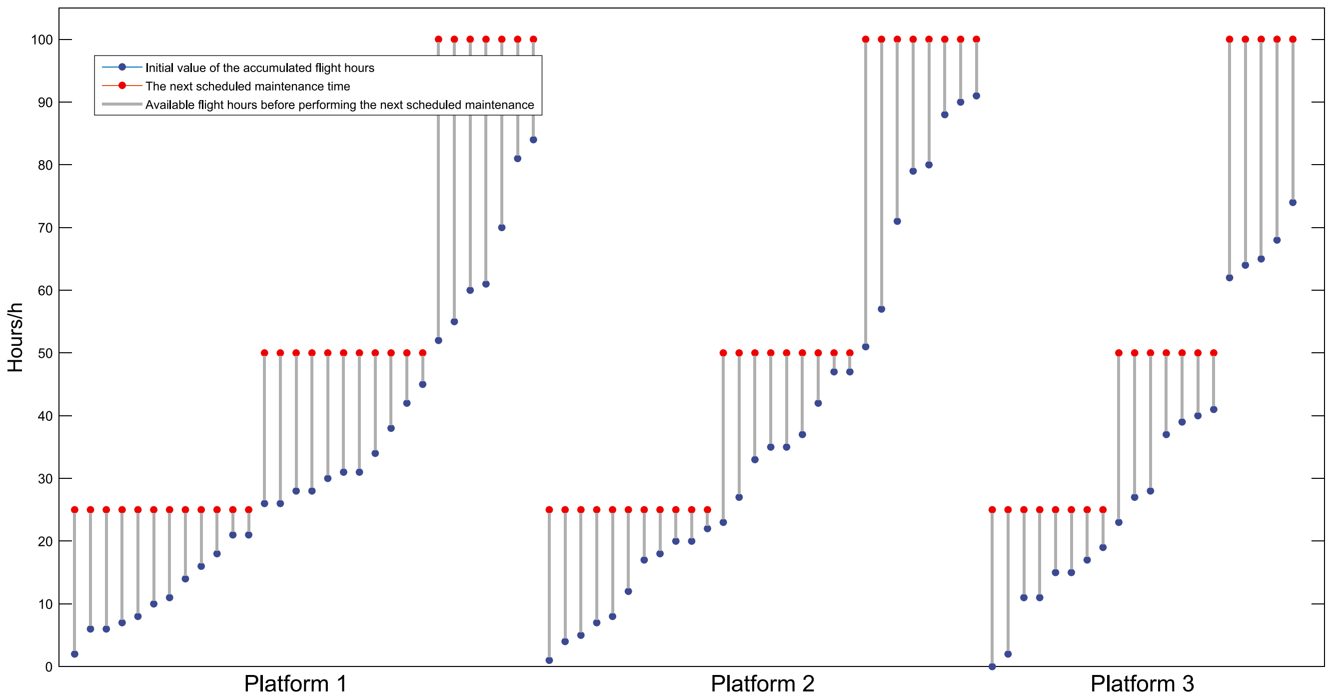


Fig. 12. Results of fleet allocation based on Θ of Case 3.

Table 6
Comparison results of optimization objects.

Comparative indicators	Case 1		Case 2		Case 3		Case 4		Case 5		Case 6	
	Bi-level	Two-stage	Bi-level	Two-stage	Bi-level	Two-stage	Bi-level	Two-stage	Bi-level	Two-stage	Bi-level	Two-stage
Objectives *F*	0.667	0.655	0.660	0.655	0.655	0.652	0.662	0.660	0.687	0.683	0.678	0.668
Differentials (%)	−1.87 %		−0.76 %		−0.47 %		−0.30 %		−0.57 %		−1.47 %	
Avg.	−0.91 %											
Calculation time (h)	19.201	0.325	23.551	0.452	26.401	0.443	24.356	0.415	12.602	0.217	17.220	0.312
Reduction (%)	98.31 %		98.08 %		98.32 %		98.30 %		98.28 %		98.19 %	
Avg.	98.25 %											

largest number of the platform. The lower-level encoding is performed separately based on the number of aircraft on the platform and corresponds to the sortie-flight planning selection priority number of each aircraft for each platform, i.e., $x_F^p = [S_1, S_2, \cdots, S_{Ni^p}]$. To satisfy these constraints, a wave mission with a larger priority number is selected first.

The evaluation index is the fitness function, and the upper-level fitness function selects the comprehensive effectiveness of the distributed platform task, *F*. By contrast, the lower-level fitness function selects the comprehensive effectiveness of the single platform, f^p.

4.2. Two-stage optimization method

As proposed in the previous section, the bi-level iteration optimization method can provide an exact solution to the problem at hand. However, the efficiency of the solution is not satisfactory due to the optimization structure being “upper-simple, lower-complex”. The upper-level fleet allocation module’s complexity is much lower than that of the lower-level sortie flight planning and maintenance scheduling modules. Each feasible solution in the upper-level module requires calling the lower-level optimization framework, which results in a nested structure. If the scheduling scale and iteration number increase excessively, then the computational volume will be unmanageable, resulting in high computational costs.

In order to address issues such as low efficiency, high cost, and unsatisfactory time efficiency related to bi-level iteration optimization method, we propose a decoupling mechanism for a two-stage optimization method. This is based on the distributed platform fleet allocation surrogate function. The two-stage optimization method has been proven to be effective in a variety of fields [60]. The second stage corresponds to the lower level of the bi-level optimization method, whereas the first stage maintains the objective function of the distributed platform fleet allocation module unchanged. It transforms the upper-level optimization mode of “random allocation - effect feedback - adjust the allocation” into a new mode that uses an allocation surrogate function. As a result, the surrogate function Θ is defined for fleet allocation on distributed platforms in the following manner:

$$\Theta = \lambda_1 \cdot \min\left(\max\left(\frac{\varphi^p}{rate\mathrm{Ta}^p}\right) - \min\left(\frac{\varphi^p}{rate\mathrm{Ta}^p}\right)\right) + \lambda_2 \cdot \min\left(\max\left(\frac{\psi^p}{rate\mathrm{Tr}^p}\right) - \min\left(\frac{\psi^p}{rate\mathrm{Tr}^p}\right)\right) + \lambda_3 \cdot \min\left(\frac{\sum_{p=1}^{\mathrm{Np}}\sum_{i=1}^{\mathrm{Ni}^p-1}\left(\mathrm{nve}\left(\mathrm{Ta}_i^p + \mathrm{Tr}_i^p - \mathrm{Ta}_{i+1}^p\right)\right)}{\sum_{p\in P}\sum_{i\in I^p}\mathrm{Tr}_i^p}\right), \tag{22}$$

where the first term in Eq. (22) represents the rule for matching the mission intensity of the distributed platform with the theoretical available hours before the fleet undergoes preventive maintenance. In Eq. (23), φ^p denotes the ratio between the average number of mission sorties of the fleet on the *p*th platform and the average mission sorties of the fleet on distributed platforms; in other words, φ^p indicates the mission intensity undertaken by the *p*th platform. In Eq. (24), $rate\mathrm{Ta}^p$ denotes the ratio between the total available flight hours before the next scheduled

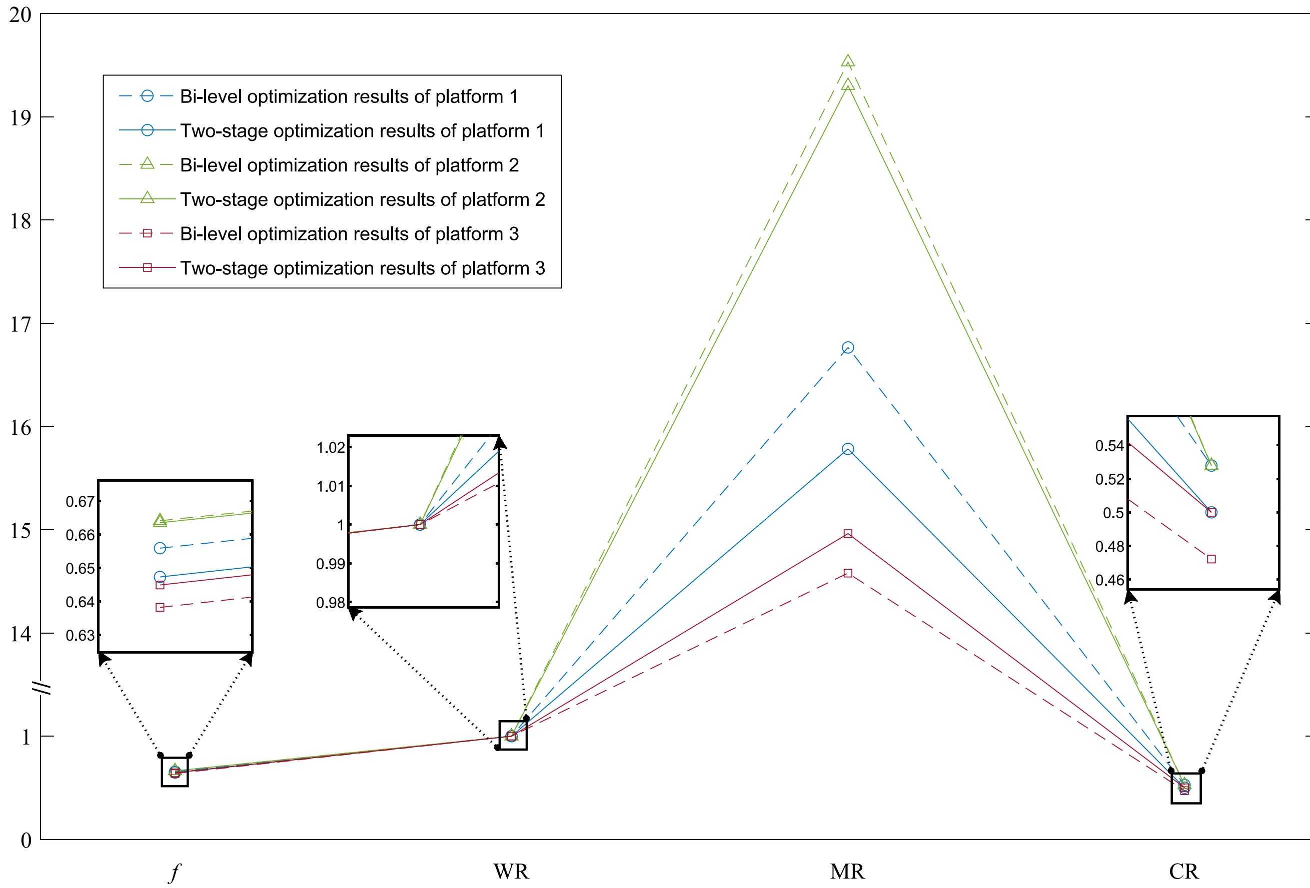


Fig. 13. Comparison results of comprehensive performance evaluation indicators for Case 3.

Table 7
The results of the ANOVA test for comparing the two methods.

Source	SS	df	MS	F	*P*-Value
Methods	0.00011	1	0.00011	0.77	0.4019
Error	0.00141	10	0.00014		
Total	0.00152	11			

maintenance of the fleet on the *p*th platform is performed and the total available flight hours before the next scheduled maintenance of the fleet on distributed platforms is performed; in other words, $rate\mathrm{Ta}^p$ indicates the sustained mission capability of the fleet on the *p*th platform. To satisfy the high-intensity mission, the fleet on the platform should avoid frequent maintenance to ensure its availability. Thus, $rate\mathrm{Ta}^p$ should not be extremely small. The functional form of the first term in Θ can match those of φ^p and $rate\mathrm{Ta}^p$.

$$\varphi^p = \frac{\frac{\mathrm{Nw}\cdot\mathrm{Nd}^p}{\mathrm{Ni}^p}}{\sum_{p\in P}\frac{\mathrm{Nw}\cdot\mathrm{Nd}^p}{\mathrm{Ni}^p}} \tag{23}$$

$$rate\mathrm{Ta}^p = \frac{\sum_{i\in I^p}\mathrm{Ta}_i^p}{\sum_{p\in P}\sum_{i\in I^p}\mathrm{Ta}_i^p} \tag{24}$$

Here, the second term in Eq. (22) represents the rule for matching the resource allocation of the distributed platform with the fleet theoretical maintenance hours. In Eq. (25), ψ^p is the ratio between the number of platform maintenance resources (referred to as the maintenance personnel herein) allocated to the *p*th platform and the total number of maintenance resources on the distributed platform; in other words, ψ^p indicates the maintenance resource allocation occupancy rate on the *p*th platform, which indirectly indicates the *p*th platform's ability to resist the load pressure on maintenance tasks. In Eq. (26), $rate\mathrm{Tr}^p$ is the ratio between the total maximum theoretical maintenance hours of the fleet on the *p*th platform and the total maximum theoretical maintenance hours of the fleet on distributed platforms; in other words, $rate\mathrm{Tr}^p$ indicates the theoretical maintenance pressure of the fleet on the *p*th platform. To balance the load of maintenance tasks, a fleet with high theoretical maintenance pressure should be assigned to a platform with high maintenance resource allocation occupancy. The functional form of the second term in Θ matches those of ψ^p and $rate\mathrm{Tr}^p$.

$$\psi^p = \frac{\sum_{k\in\mathrm{Kc}}|\mathrm{Lp}_k^p|}{\sum_{p\in P}\sum_{k\in\mathrm{Kc}}(|\mathrm{Lp}_k^p|)} \tag{25}$$

$$rate\mathrm{Tr}^p = \frac{\sum_{i\in I^p}\mathrm{Tr}_i^p}{\sum_{p\in P}\sum_{i\in I^p}\mathrm{Tr}_i^p} \tag{26}$$

Here, the second term in Eq. (22) represents the control rule for the fleet echelon usage time interval on a distributed platform. By implementing fleet echelon usage control, each aircraft is sorted based on the available hours (i.e., the available hours prior to the commencement of preventive maintenance) and presents an echelon arrangement, which implies that the available hours maintain a certain interval with each other. The purpose of echelon usage interval time is to provide a reference for the flight planning of the aircraft to ensure that the fleet completes the mission while dispersing the maintenance timing of each aircraft, to avoid the concentration of maintenance tasks, and to ensure that the normal execution of combat and training missions is unaffected. Therefore, the control rule for the fleet echelon usage time interval must be considered during fleet allocation. $\mathrm{Ta}_i^p + \mathrm{Tr}_i^p - \mathrm{Ta}_{i+1}^p$ indicates that, after fleet sorting is performed on the *p*th platform, the sum of available and theoretical maintenance hours exceeds the available hours of the

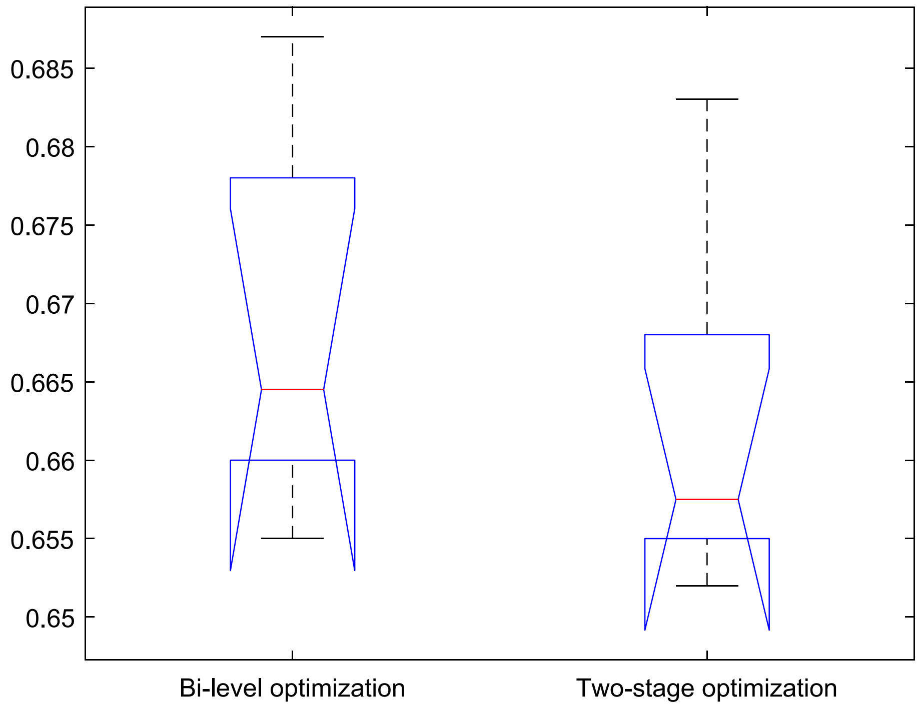


Fig. 14. Comprehensive effectiveness of distributed platform task F of both methods in six cases.

latter aircraft. It signifies the theoretical duration in which the overlap of maintenance tasks can occur between two aircraft. The non-negative function $\mathrm{nve}(\cdot)$ is defined in Eq. (27). Subsequently, $\mathrm{nve}(\cdot)$ is combined with $\mathrm{Ta}_i^p + \mathrm{Tr}_i^p - \mathrm{Ta}_{i+1}^p$. $\sum_{p=1}^{\mathrm{Np}}\sum_{i=1}^{\mathrm{Ni}^p-1}\left(\mathrm{nve}\left(\mathrm{Ta}_i^p + \mathrm{Tr}_i^p - \mathrm{Ta}_{i+1}^p\right)\right)$ indicates the sum of overlap durations of theoretical maintenance tasks on the pth platform. $\sum_{p\in P}\sum_{i\in I^p}\mathrm{Tr}_i^p$ indicates the sum of overlap durations of theoretical maintenance tasks on the distributed platforms. Therefore, after dividing $\sum_{p=1}^{\mathrm{Np}}\sum_{i=1}^{\mathrm{Ni}^p-1}\left(\mathrm{nve}\left(\mathrm{Ta}_i^p + \mathrm{Tr}_i^p - \mathrm{Ta}_{i+1}^p\right)\right)$ by $\sum_{p\in P}\sum_{i\in I^p}\mathrm{Tr}_i^p$, a dimensionless ratio is obtained. The smaller the ratio, the better is the theoretical effect of the control rule for the fleet echelon usage time interval.

$$\mathrm{nve}(x) = \begin{cases} 0, & x \leqslant 0 \\ x, & x > 0 \end{cases} \tag{27}$$

Here, λ_1, λ_2, and λ_3 are the weights of the three rule terms, whose values can be specified by the decision maker based on to their importance. The surrogate function for fleet allocation Θ on distributed platforms is used as the objective function for fleet allocation on the distributed platform, and a feasible allocation scheme can be solved using an evolutionary algorithm.

4.3. Distributed repair task allocation heuristic rules

The heuristics rules for the allocation of distributed repair tasks require the load balancing of maintenance and repair tasks between distributed platforms with the minimum number of repair task transfers after the allocation is performed. The abovementioned heuristic rules are defined as shown in Eq. (28).

$$\min\left\{\sum_{p\in P}\mathrm{abs}\left(\mathrm{Nr}_t^p - \mathrm{Ns}_t^p\right)\middle|\min\left(\max\eta_t^p - \min\eta_t^p\right)\right\}, \tag{28}$$

where $\mathrm{abs}(\cdot)$ denotes the absolute value function. $\left(\mathrm{Nr}_t^p - \mathrm{Ns}_t^p\right)$ indicates the number of aircraft to be repaired before and after the distributed repair task allocation on the pth platform at the moment t. $\sum_{p\in P}\mathrm{abs}\left(\mathrm{Nr}_t^p - \mathrm{Ns}_t^p\right)$ contains information regarding the number of repair task allocation transfers between distributed platforms. In Eq. (29), η_t^p indicates the maintenance resource occupancy rate on the pth platform at moment t. The term $\min\left(\max\eta_t^p - \min\eta_t^p\right)$ can realize the load balancing of distributed platform maintenance and repair tasks after task allocation.

$$\eta_t^p = \sum_{l\in \mathrm{Lp}_k^p}\sum_{k\in \mathrm{Kc}}\sum_{(i,j)\in A_t^p}\frac{\mathrm{Xp}_{ijkl}^p}{\left|\mathrm{Lp}^p\right|}, \forall p \in P \tag{29}$$

Subsequently, the following supplementary rules must be incorporated into Eq. (28):

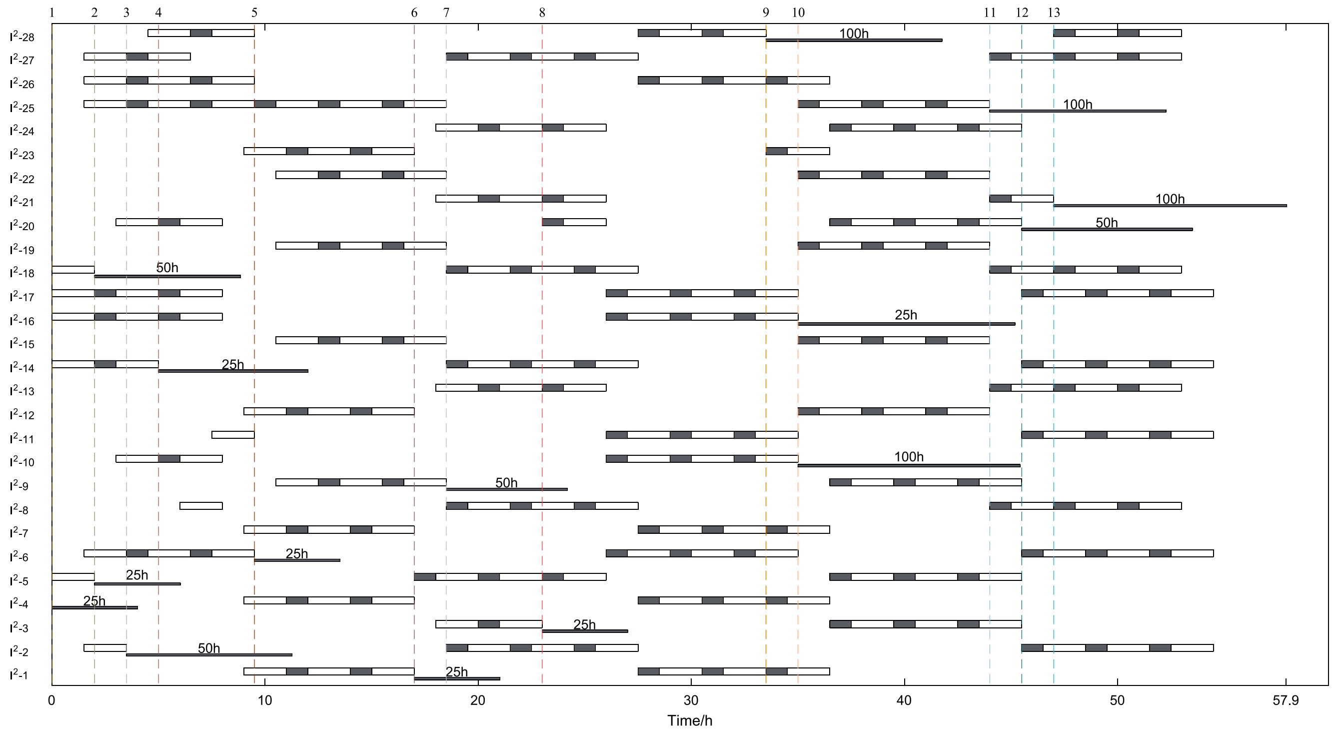
i. Scheduled maintenance tasks cannot be transferred, unlike repair tasks.
ii. The number selection rule for transferring fault repair tasks and replenishing the available aircraft is first set to a small value of aircraft number by default.
iii. The heuristic rules for task allocation in distributed repair are relatively simple but can be used to perform an exhaustive search for the optimal solution.

5. Case study

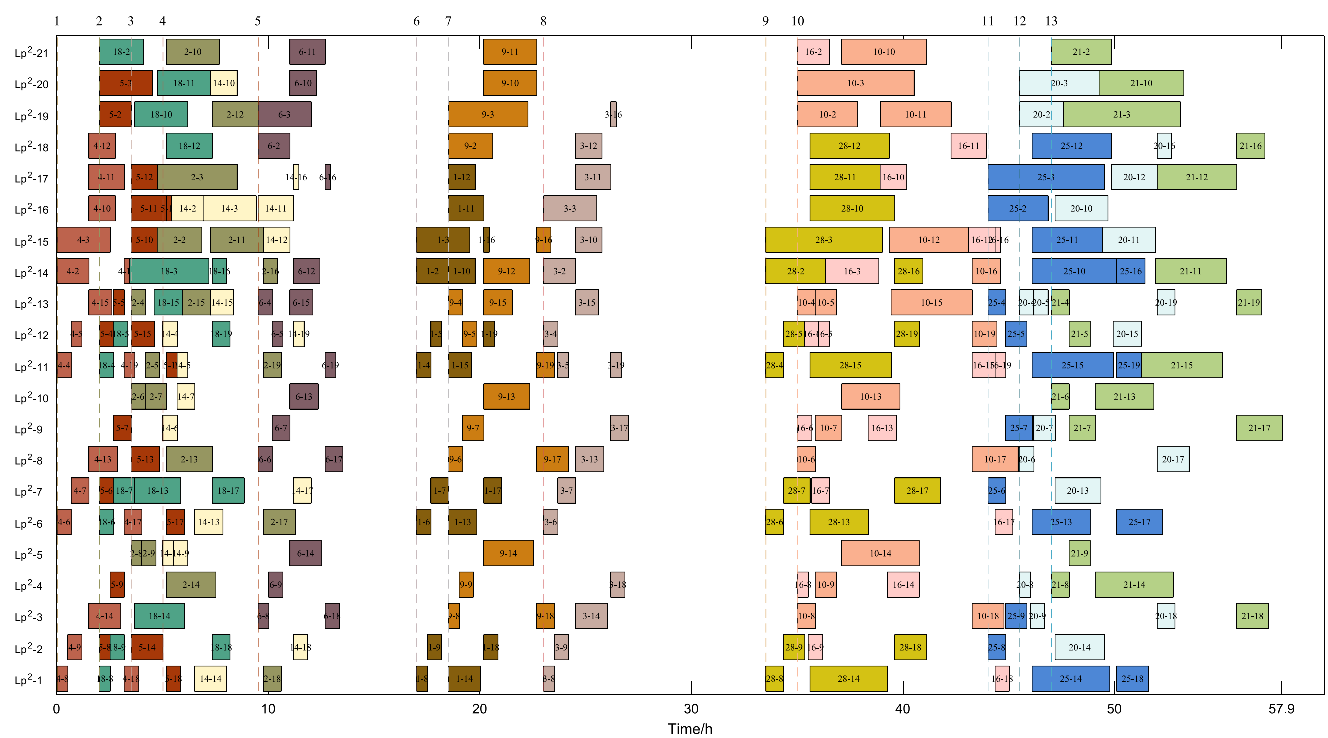
5.1. Mission case generation

A mission case was constructed using three large distributed ship platforms to execute a certain high-intensity continuous sortie combat and training mission. The algorithms used were based on MATLAB 2020a programming, and a personal computer (Windows 7 64-bit operating system, Intel(R) Xeon(R) Gold 5122 CPU @ 3.60 GHz, 32 G memory) was used to perform the calculation. Each algorithm was executed 20 times independently, and the resulting data were recorded.

The mission flight planning parameters were set as follows: number of sortie waves, $\mathrm{Nw}^1 = \mathrm{Nw}^2 = \mathrm{Nw}^3 = 36$; number of platforms $\mathrm{Np} = 3$; number of carrier aircraft on the pth platform, $\mathrm{Ni}^1 = 30$, $\mathrm{Ni}^2 = 28$, and $\mathrm{Ni}^3 = 20$; number of continuous cyclic sorties on the pth platform, $\mathrm{Nc}^1 = 4$, $\mathrm{Nc}^2 = 3$, and $\mathrm{Nc}^3 = 2$; number of formations of cyclic sorties



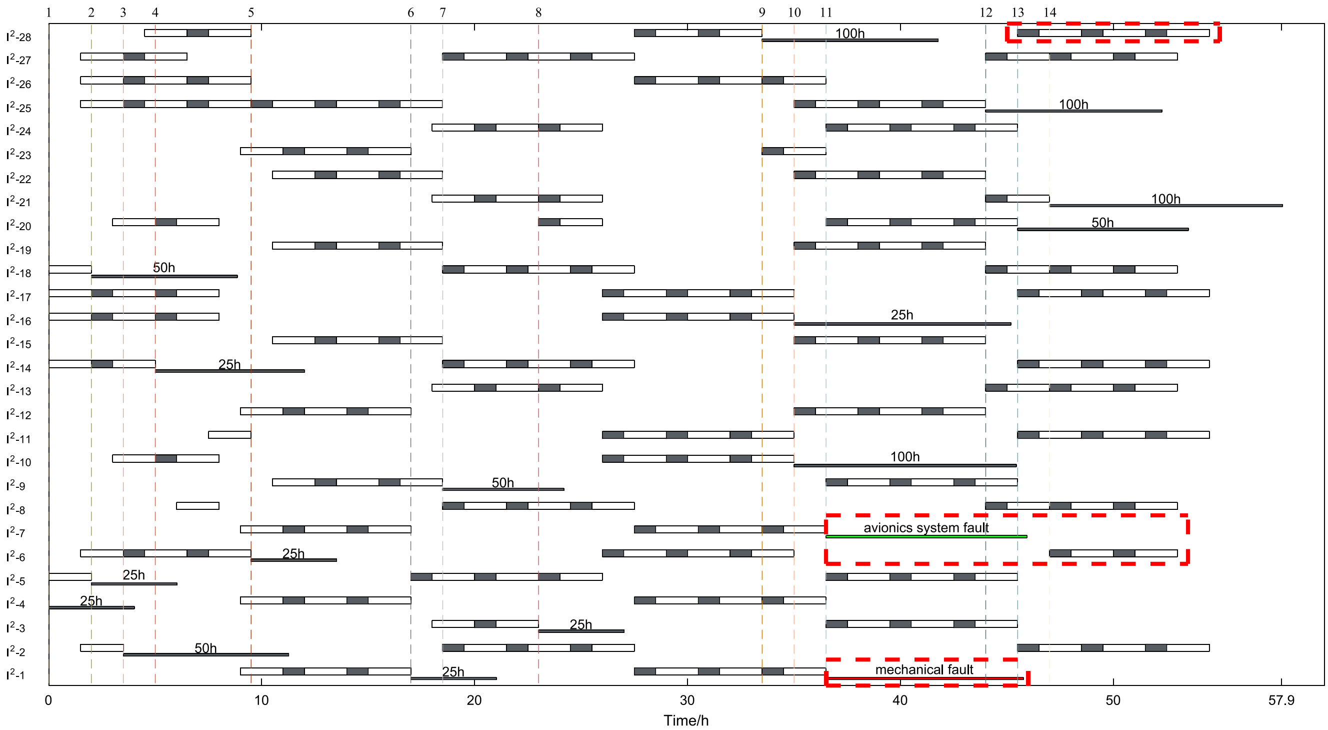
(*a*) Gantt chart showing sortie flight planning scheme



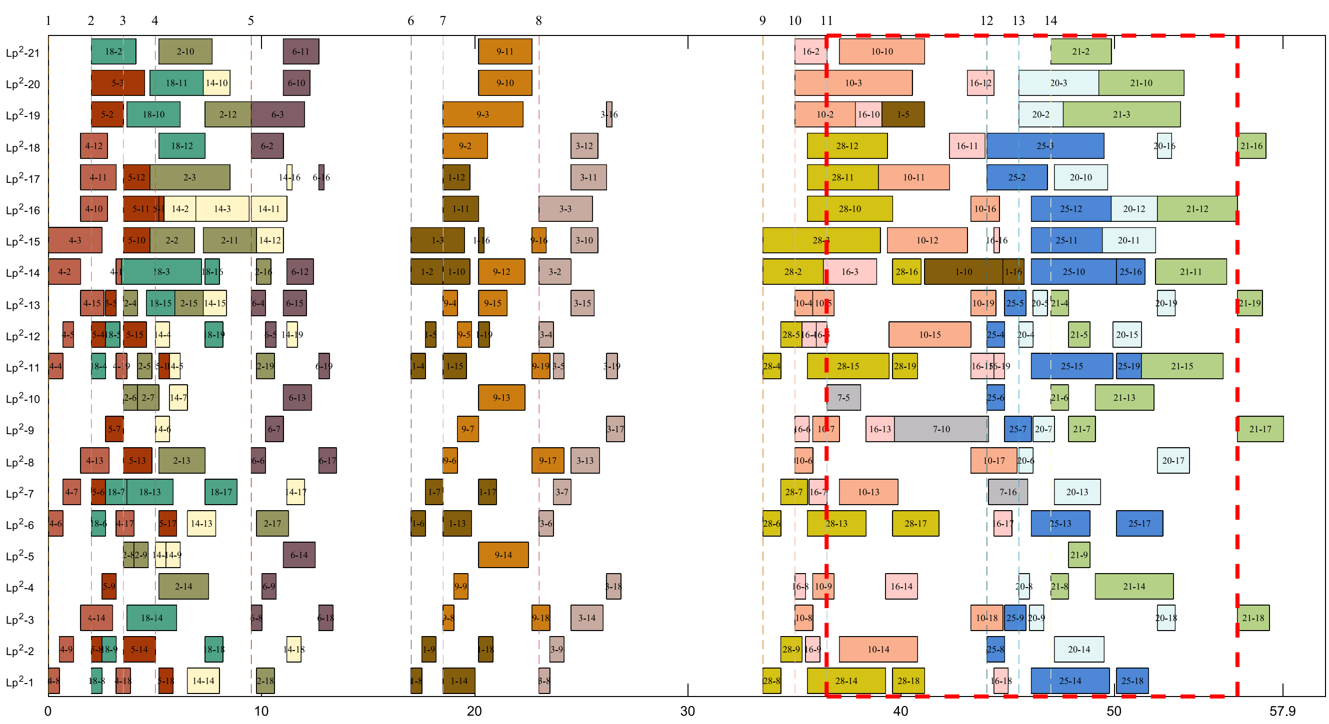
(*b*) Gantt chart showing maintenance scheme

Fig. 15. Baseline scheduling Gantt chart of Case 3 (Platform 2).

on the pth platform, $\mathrm{Ng}^1 = \mathrm{Ng}^2 = \mathrm{Ng}^3 = 2$; number of carrier-based aircraft required for the wave sortie on the pth platform, $\mathrm{Nd}^1 = 8$, $\mathrm{Nd}^2 = 5$, and $\mathrm{Nd}^3 = 4$; flight mission duration on the pth platform, $\mathrm{Tw}^1 = \mathrm{Tw}^2 = \mathrm{Tw}^3 = 2$; deck cycle duration on the pth platform, $\mathrm{Td}^1 = \mathrm{Td}^2 = \mathrm{Td}^3 = 1.5$; deck operation duration on the pth platform, $\mathrm{To}^1 = \mathrm{To}^2 = \mathrm{To}^3 = 1$; impact weight of each platform, $\nu^1 = 0.5$, $\nu^2 = 0.3$, and $\nu^3 = 0.2$; weight of effectiveness evaluation indicator, $\gamma_1 = 0.5$, $\gamma_2 = 0.003$, and $\gamma_3 = 0.2$; weights of the three rules terms in Θ, $\lambda_1 = 0.3$, $\lambda_2 =$



(*a*) Gantt chart showing sortie flight planning scheme



(*b*) Gantt chart showing maintenance and repair scheme

Fig. 16. Non-transfer repair reactive scheduling Gantt chart of Case 3 (Platform 2).

0.3, and $\lambda_3 = 0.4$.

The maintenance and repair task parameters were set as follows: Number of skill categories $Kc = \{1, 2, 3, 4\}$ for special equipment, avionics, ordinance, and machinery specialties, respectively; number of maintenance personnel on three platforms, i.e., $[|Lp_1^*|, |Lp_2^*|, |Lp_3^*|, |Lp_4^*|]$, is $[5, 6, 4, 10]$, $[5, 5, 3, 8]$, and $[4, 5, 3, 7]$, respectively; maintenance and repair modes M1–M6, which correspond to six modes of 25, 50, and 100 flight-hour maintenance,

Table 8
Repair task transfer records of Case 3.

Transfer time (h)	24.5	35	47	48.5
Fault modes	M5	M5	M6	M6
Transfer from platform no.	1	1	1(3)	1
Faulty aircraft no.	26	25	1	2
Transfer to platform no.	2	3	2	2
Supplementary aircraft no.	25	1	3	5

mechanical faults, avionics system faults, and special equipment faults, respectively. The maintenance operation of the AoN network is shown in Fig. 8, in which operations 1 and 20 are virtual starting and ending operations and services for integrating and connecting all operations, respectively. The operating hours for the maintenance and repair operations are listed in Table 4.

The parameters involved in the optimization algorithm were set as follows: For the bi-level algorithm, in the upper-level algorithm, the number of iterations $G_u = 16$; population size $N_{popu} = 20$; crossover probability $p_{cu} = 0.5$; mutation probability $p_{mu} = 0.1$. In the lower-level algorithm, the number of iterations $G_l = 30$; population size $N_{popl} = 40$; crossover probability $p_{cl} = 0.5$; mutation probability $p_{ml} = 0.1$. For the two-stage algorithm, the number of iterations $G_a = 50$; population size $N_{popa} = 20$; crossover probability $p_{ca} = 0.5$; mutation probability $p_{ma} = 0.1$.

Six groups of cases were established in the mission, as shown in Fig. 9 with an initial difference in the accumulated flight hours of the fleet. In the figure, "+" indicates the median and " × " denotes the mean. Case 6, 5, 1, 2, 4 and 3 show that the distribution of available hours before the next scheduled maintenance is concentrated at low values, which indicates that the aircraft will undergo scheduled maintenance more frequently and earlier in the latter cases, and the maintenance task load pressure of the platform hangar bay increases in that order. In Case 3, the solution performance of the proposed algorithm for the DP-ASMS was evaluated under decreasing fleet availability and the large-scale reactive rescheduling of fleet maintenance and repair tasks, which is the focus of the case study performed.

5.2. Comparison and analysis of two optimization methods

5.2.1. Results of bi-level iterative optimization method

In this study, the baseline scheduling scheme for wave sorties and maintenance of distributed platforms was solved using the bi-level iterative optimization method based on the model expressed in Eq. (18). The study did not consider random faults or battle damage of carrier-based aircraft and cross-platform linkage mechanism. Fig. 10 shows the Gantt chart for the scheduling scheme, using Platform 3 of Case 3 as an example. The Gantt chart indicates that the maintenance load dispersion rate and the completion rate of continuous cyclic sorties were well-performed when the bi-level iterative optimization method was used. The maintenance scheduling scheme underwent four reactive reschedulings at the starting moments of the fourth, sixth, seventh, and ninth maintenance. Upon inspection, the scheduling scheme shown in the Gantt chart satisfies the modeling constraints, validating the model and proving the optimization method's effectiveness.

The results of fleet allocation for Platform 3 are shown in Fig. 11. A comparison between Fig. 11(a) and Fig. 9(a) shows that the accumulated flight hour allocation results of Platform 3 in the six groups of cases are similar to the distribution of the initial values. Regularity was not observed in the actual and allocated values. Meanwhile, a comparison between Fig. 11(b) and Fig. 9(b) shows regularity: the available flight hours before the next scheduled fleet maintenance on Platform 3 in all six groups of cases indicated a median and a mean decrease compared with the initial value. Meanwhile, based on Table 5, the optimization objectives were the largest in Case 5, whereas the smallest were in Case 3. The essence of optimizing the fleet platform allocation is not to achieve the actual value of the fleet flight hours but the available time before performing the next scheduled maintenance of the fleet corresponding to each carrier-based aircraft Ta_i^p. The higher the Ta_i^p, the greater is the improvement in the WR, MR, and CR, and the higher are the values of effectiveness evaluation indices F and f. Platform 3 has a low sortie pressure for flight missions and a sufficient number of maintenance personnel. There is also an insignificant demand for the available hours before the next scheduled maintenance, which means the allocation value is lower than the overall level. Additionally, the available hours before the next scheduled maintenance are almost evenly distributed and arranged in an echelon pattern, as expected. These results further confirm the reasonableness of the surrogate function Θ for fleet allocation on distributed platforms.

5.2.2. Results of two-stage optimization method

The two-stage optimization method involves using a surrogate Θ fleet allocation on distributed platforms to solve the baseline scheduling scheme for wave sorties and perform maintenance on distributed platforms. For example, the allocation result using the two-stage optimization method is shown in Fig. 12 based on Case 3. As explained in the previous section, the fleet platform is allocated based on the available flight hours before the next scheduled maintenance. This allocation result is then used in the lower-level algorithm for fleet sortie and maintenance integrated scheduling.

5.2.3. Comparison result analysis

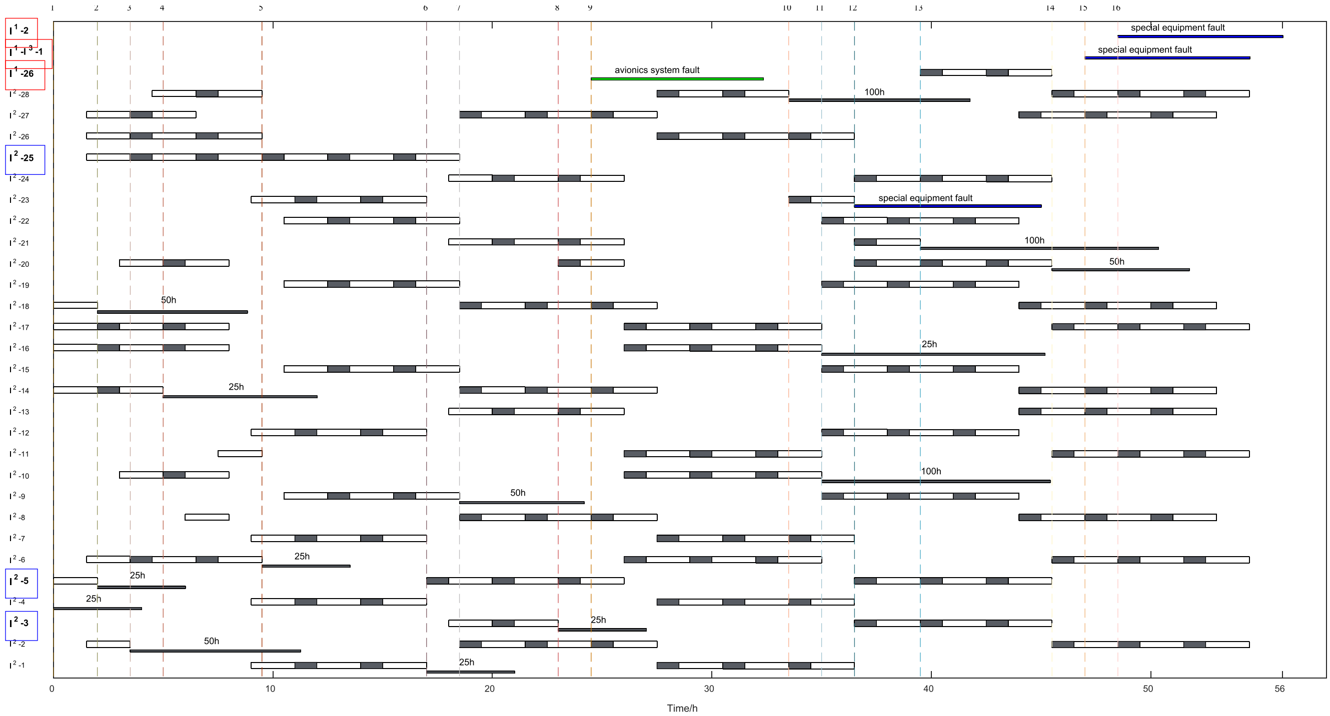
Using Case 3 as an example, a comparison experiment was conducted between the bi-level and two-stage optimization methods. A comparison of the optimal results yielded by the two methods in terms of the optimization objectives F and the calculation time is shown in Table 6, whereas that in terms of optimization objective f is shown in Fig. 13. We can find that (from the non-statistical point of view), the proposed two-stage optimization method yields highly congruent scheduling results across optimization objectives such as F, f, WR, MR, and CR, when compared to the precision method of bi-level iterative optimization. The optimal results of optimization objectives F and f obtained via the two methods differed by 1 %–2%.

In order to provide statistical evidence for our claim, we ran ANOVA tests on both methods. The results of these tests are summarized in Table 7. Fig. 14 shows the comprehensive effectiveness of distributed platform task F of both methods in six cases. Based on the results of the F-test, we can conclude that there is no significant difference in the objective function results obtained by the two methods. The P-value of the F-test is greater than 0.05, which means that the null hypothesis H0 is accepted at a significance level of $\alpha = 0.05$. Specifically, the F_{actual} value of 0.77 is less than the critical value of 5.117 in the F-test critical value table. This aligns with our expectations and reinforces the effectiveness of the simplification method. Therefore, we can confirm that there is no significant difference in accuracy between the two methods.

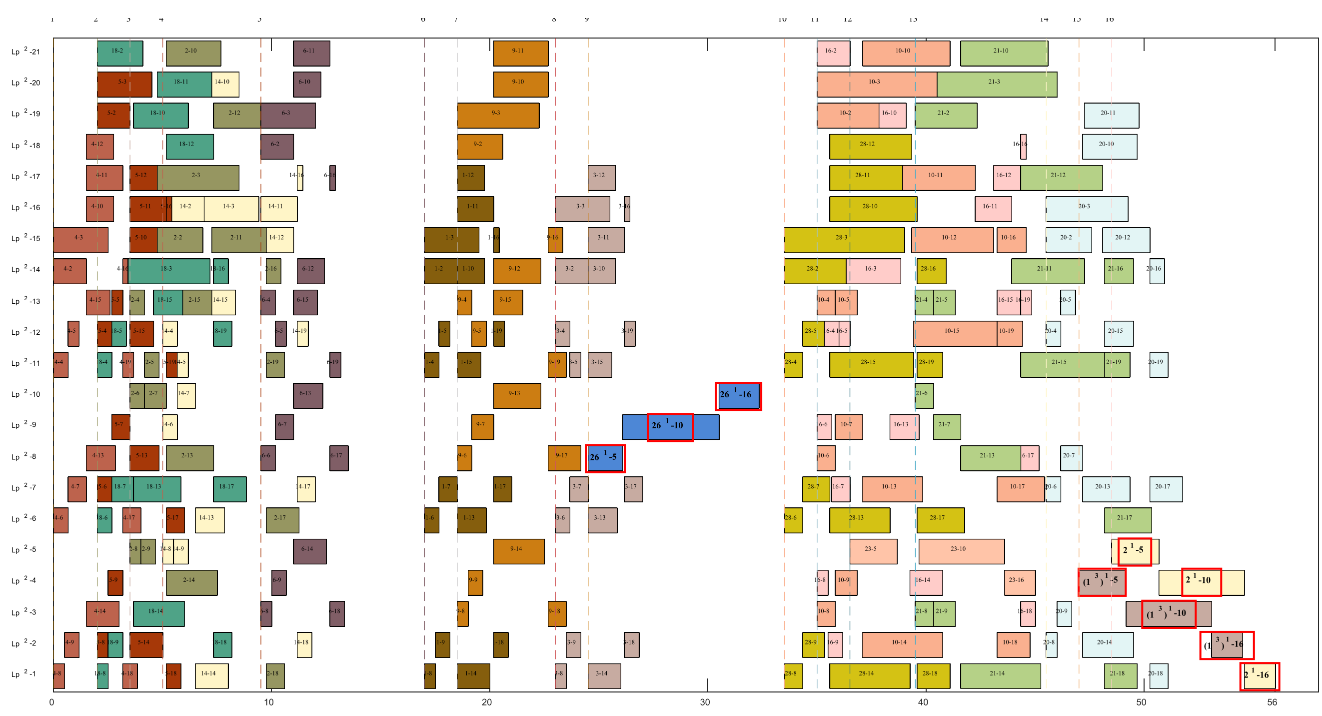
By contrast, the two-stage optimization method was found to significantly reduce the calculation time, as compared to bi-level iteration optimization method. As a result, the comparison results confirmed the effectiveness of this method in fleet allocation on a distributed platform. The surrogate function Θ used in this method helps to simplify the complex iterations of the bi-level optimization framework, which reduces the calculation cost and improves the scheduling efficiency while ensuring optimal performance. The method will be successfully apply in the rapid formulation of integrated scheduling for fleet wave sorties and the maintenance of naval distributed platforms.

5.3. Comparison of cross-platform linkage mechanism

Using Case 3 as an example, random fault or battle damage on the fleet and cross-platform linkage mechanism are considered. First, using the two-stage optimization method for the model expressed in Eq. (18), the baseline scheduling scheme for the integrated scheduling of fleet



(*a*) Gantt chart showing sortie flight planning scheme



(*b*) Gantt chart showing maintenance and repair scheme

Fig. 17. Repair task transfer reactive scheduling Gantt chart of Case 3 (Platform 2).

wave sorties and the maintenance of naval distributed platforms were solved. The results of the baseline scheduling scheme for Platform 2 are shown in Fig. 15. Second, using the baseline scheduling scheme, a probability-triggered random fault or battle damage was added to simulate marine engagement in the distributed platform. The occurrence of dynamic uncertainty disturbances, such as faults or battle damage, affects the execution of the subsequent baseline flight planning. Therefore, reactive adjustments to the planning are required after the perturbations, and perturbation-adjusted flight planning will change locally from the baseline schedule.

Table 9
Comparison results of cross-platform linkage mechanism and single-platform independent repair.

Cases	Platforms	Indicators	Cross-platform linkage mechanism				Single-platform independent repair			
			f	WR	MR	CR	*f*	WR	MR	CR
Case 1	Platform 1	*Best.*	**0.642**	**1**	**13.943**	**0.500**	0.572	0.944	13.171	0.278
		Avg.	**0.625**	**1**	**14.133**	**0.413**	0.567	0.926	13.016	0.352
		Var.	**1.62E-04**	**0**	**4.81E-01**	**4.28E-03**	3.77E-04	5.14E-04	8.77E-01	6.69E-03
	Platform 2	*Best.*	**0.635**	**1**	**14.430**	**0.459**	0.618	**1**	15.195	0.361
		Avg.	**0.621**	**1**	**14.316**	**0.389**	0.617	**1**	13.469	0.382
		Var.	9.98E-05	**0**	2.051	2.08E-03	**1.40E-06**	**0**	**1.429**	**1.93E-04**
	Platform 3	*Best.*	**0.640**	**1**	**14.316**	**0.444**	0.630	**1**	13.700	**0.444**
		Avg.	**0.632**	**1**	**14.430**	0.430	0.624	**1**	12.518	**0.431**
		Var.	5.02E-05	**0**	**2.051**	7.57E-04	**2.38E-05**	**0**	4.688	**5.28E-04**
Case 2	Platform 1	*Best.*	**0.641**	**1**	**17.471**	**0.444**	0.571	**1**	14.402	0.139
		Avg.	**0.622**	**1**	**16.501**	**0.365**	0.568	0.972	14.457	0.278
		Var.	7.16E-05	**0**	5.48E-01	**1.43E-03**	**1.37E-05**	1.54E-03	**6.07E-03**	6.17E-03
	Platform 2	*Best.*	**0.633**	**1**	**14.705**	0.444	0.622	**1**	14.801	**0.528**
		Avg.	**0.627**	**1**	**14.888**	0.412	0.621	**1**	14.264	**0.435**
		Var.	1.57E-05	**0**	7.09E-01	**5.05E-04**	**3.98E-06**	**0**	**4.42E-01**	6.43E-03
	Platform 3	*Best.*	**0.638**	**1**	**16.481**	**0.444**	0.626	**1**	16.068	0.389
		Avg.	**0.628**	**1**	**16.295**	**0.400**	0.619	0.999	15.554	0.364
		Var.	2.61E-05	**0**	1.850	7.67E-04	**2.47E-05**	2.86E-05	**4.81E-01**	**7.32E-04**
Case 3	Platform 1	*Best.*	**0.626**	**1**	**16.049**	**0.389**	0.549	0.889	14.513	0.306
		Avg.	**0.599**	**0.997**	**14.068**	**0.292**	0.518	0.861	13.610	0.233
		Var.	**1.63E-04**	**9.00E-05**	1.420	**2.26E-03**	5.23E-04	8.82E-04	**7.28E-01**	3.73E-03
	Platform 2	*Best.*	**0.644**	**1**	**16.556**	**0.472**	0.639	**1**	14.939	**0.472**
		Avg.	**0.634**	**1**	**15.875**	**0.434**	0.631	**1**	15.844	0.417
		Var.	9.72E-05	**0**	**4.48E-01**	2.15E-03	**3.82E-05**	**0**	1.766	**1.04E-03**
	Platform 3	*Best.*	**0.635**	**1**	**13.480**	**0.472**	0.629	**1**	11.536	**0.472**
		Avg.	**0.628**	**1**	**13.797**	**0.431**	0.624	**1**	12.766	0.430
		Var.	5.32E-05	**0**	**6.72E-01**	1.13E-03	**1.04E-05**	**0**	1.306	**3.10E-04**
Case 4	Platform 1	*Best.*	**0.630**	**1**	**15.716**	**0.417**	0.622	1	14.589	0.389
		Avg.	0.600	0.976	**15.317**	**0.331**	**0.609**	**0.983**	14.943	0.325
		Var.	2.38E-04	1.23E-03	**1.93E-01**	3.35E-03	**3.34E-05**	**9.64E-04**	3.83E-01	**1.08E-03**
	Platform 2	*Best.*	**0.648**	**1**	**15.843**	**0.500**	0.637	**1**	14.075	0.472
		Avg.	**0.639**	**1**	**15.162**	0.466	0.632	**1**	14.233	**0.472**
		Var.	2.85E-05	**0**	1.440	**6.84E-04**	**1.57E-05**	**0**	**7.80E-01**	1.93E-03
	Platform 3	*Best.*	**0.640**	**1**	**16.915**	**0.444**	0.630	**1**	15.410	0.417
		Avg.	**0.631**	**1**	**15.000**	**0.429**	0.620	0.999	14.819	0.379
		Var.	**8.51E-06**	**0**	9.03E-01	**1.98E-04**	1.11E-04	2.97E-05	**6.24E-01**	2.10E-03
Case 5	Platform 1	*Best.*	**0.669**	**1**	**15.581**	**0.611**	0.653	**1**	14.073	0.556
		Avg.	**0.657**	**1**	**15.078**	**0.558**	0.647	**1**	14.298	0.522
		Var.	**8.00E-05**	**0**	**4.10E-01**	**1.62E-03**	1.60E-04	**0**	6.39E-01	3.28E-03
	Platform 2	*Best.*	**0.646**	**1**	**15.326**	**0.500**	0.640	**1**	13.363	**0.500**
		Avg.	**0.645**	**1**	**15.364**	**0.494**	0.635	**1**	12.837	0.485
		Var.	4.12E-05	**0**	**9.98E-01**	**6.52E-04**	**1.60E-05**	**0**	2.229	5.26E-04
	Platform 3	*Best.*	**0.670**	**1**	**19.583**	0.556	0.667	**1**	16.720	**0.583**
		Avg.	**0.645**	**1**	**15.120**	**0.497**	0.640	**1**	13.938	0.493
		Var.	1.14E-04	**0**	**3.903**	**7.63E-04**	**5.08E-05**	**0**	4.003	8.02E-04
Case 6	Platform 1	*Best.*	**0.654**	**1**	**17.845**	0.500	0.632	**1**	16.079	**0.583**
		Avg.	**0.649**	**1**	**17.438**	**0.481**	0.622	0.997	16.180	0.434
		Var.	**2.11E-05**	**0**	1.290	**2.06E-04**	7.83E-05	1.40E-04	**2.38E-01**	7.68E-03
	Platform 2	*Best.*	**0.645**	**1**	**15.151**	**0.500**	0.639	**1**	14.908	0.472
		Avg.	**0.638**	**1**	**15.370**	**0.462**	0.635	**1**	15.237	0.444
		Var.	3.67E-05	**0**	1.980	9.27E-04	**1.39E-05**	**0**	**1.570**	**3.09E-04**
	Platform 3	*Best.*	**0.641**	**1**	**15.421**	**0.472**	0.636	**1**	15.628	0.444
		Avg.	**0.638**	**1**	**15.131**	**0.463**	0.625	**1**	14.410	0.409
		Var.	**5.60E-06**	**0**	**5.32E-01**	**2.06E-04**	9.50E-05	**0**	1.450	1.43E-03

To verify the superiority of the cross-platform linkage mechanism under dynamic uncertainty repair task conditions, the cross-platform linkage mechanism was compared with the single-platform independent repair. The random fault probability of aircraft was set to 0.1, and the battle damage probability of aircraft on Platform 1 was set to 0.3. Subsequently, the integrated scheduling scheme of flight planning and the independent maintenance and repair for Case 3 (Platform 2) were calculated under single-platform independent repair conditions. The flight-planning results are shown in Fig. 16(a). The dotted red box in the figure represents the position where the scheme changes. Compared with the baseline flight planning shown in Fig. 15(a), the avionics system fault and mechanical fault of the seventh and first aircraft occurred at the beginning of the 11th maintenance or repair, respectively. Therefore, the algorithm selects the 28th aircraft for a slight complementary adjustment correction to satisfy the mission requirements for the subsequent sortie planning affected by the fault. Simultaneously, reactive adjustments were performed to accommodate the effects of the maintenance scheme shown in the Gantt chart in Fig. 15(b), and the results are shown in Fig. 16(b).

Dynamic DP-ASMS modeling based on Eq. (21) uses the two-stage optimization method to perform reactive scheduling adjustment calculations for the cross-platform maintenance linkage mechanism against the baseline scheduling scheme. The repair task transfer records of Case 3 are listed in Table 8. The data in the first column show that at the mission time of 24.5 h, the 26th aircraft of Platform 1 exhibited an avionics system fault, and the repair task was transferred to Platform 2. Simultaneously, the 25th aircraft of Platform 2 as the supplementary aircraft was replenished to Platform 1 to maintain the number of aircraft on the platform. A Gantt chart showing the sortie-flight planning scheme for Platform 2 is presented in Fig. 17(a). The red rectangle in the figure signifies aircraft transfer to Platform 2, and the blue rectangle signifies aircraft transfer from Platform 2. The figure shows that the repair tasks of the 26th, 1st (initially docked on Platform 3), and 2nd aircraft on Platform 1 were transferred to Platform 2. Simultaneously, the 25th, 3rd, and 5th aircraft on Platform 2 were transferred as supplementary aircraft to Platform 1. The 23rd aircraft on Platform 2 exhibited a specific equipment fault and thus was not assessed as a repair task transferred to other platforms; therefore, it is not shown in Table 8. The results of the maintenance and repair scheme presented in a Gantt chart are shown in Fig. 17(b). An analysis of the results shows that the complexity of the scheduling scale increased significantly after random faults or battle damage were incorporated and that the maintenance and repair scheduling process underwent 13 reactive reschedulings, i.e., at the 2nd, 3rd, 4th, 5th, 7th, 8th, 9th, 11th, 12th, 13th, 14th, 15th, and 16th maintenance and repair starting moments. Reactive reschedulings were performed at the 9th, 15th, and 16th maintenance and repair starting moments for repair tasks from other platforms. Based on testing, the scheduling scheme shown in the Gantt chart satisfied all the constraints of the modeling and validated the cross-platform maintenance linkage mechanism in the modeling.

The complete statistics of the calculation results pertaining to the cross-platform linkage mechanism and single-platform independent repair scheduling are shown in Table 9. The bold values in the table indicate a better solution for the same set of comparison experiments, and *Var.* indicates the variance of the results of multiple calculations. The following conclusions were inferred based on the calculation results:

i. The cross-platform linkage mechanism, which is based on heuristic rules for task allocation in distributed repair, transfers repairing tasks of faulty or battle-damaged aircraft to platforms with lower maintenance loads, thus dispersing the maintenance load and increasing the MR.
ii. For Platform 1, which has a high fault probability and is subjected to high mission intensity and theoretical maintenance requirements in cases 2 and 3, the heuristic rules of the cross-platform linkage mechanism transfer the repair tasks and supplement available aircraft to satisfy the fleet availability. This ensures stable completion of the mission wave with full formation, thereby increasing the WR metrics.
iii. The cross-platform linkage mechanism's stable WR and the advantage of CR indicators ensure the stability of combat and training missions and deck operations. The mechanism's advantages in MR, CR, and CR indices improve the evaluation index f compared to single-platform independent repair. However, due to the scheduling process's high complexity and uncertainty, the results' dispersion under some case platforms was greater than that of single-platform independent repair, and the stability of the results was slightly weaker, showing the suboptimality of $f_{var.}$ in some cases.
iv. Single-platform independent repair for high-intensity maintenance concentrates maintenance loads in the hangar bay, leading to a backlog of maintenance and repair tasks, unsatisfactory task timeliness, and a missing wave that results in a WR of less than 1. Compared to this, the cross-platform linkage mechanism's f and MR indices are superior. However, because the mother platform was used for repair to avoid breaking the original platform used for the aircraft's continuous cyclic sortie process, maintenance task transfer, and other laborious and complex processes, the scheduling results were slightly more stable, as indicated by the f and CR metrics.

6. Managerial insights

Multiple managerial insights can be gained from the devised model, the suggested optimization algorithm, and the performed analysis in our study. The military is facing the challenge of adapting to complex and ever-changing modern combat environments, as well as new operational concepts. It is necessary to have adaptable, prompt, agility and tailored responses to meet mission demands. To achieve this, effective orchestration of operational command and maintenance support management activities across various platforms within a multi-platform system is needed.

In the first place, we have created a comprehensive mathematical model for scheduling the deployment, operations, and maintenance of carrier-based aircraft. The model is designed to support decision makers in creating fleet allocation plans, devising sortie flight schedules, and scheduling cooperative repairs for future maritime distributed operations, which improve performance metrics while adhering to time and resource constraints.

Subsequently, in this research, we propose a novel model that utilizes state-of-the-art algorithms to improve upon traditional manual empirical scheduling methods. One of our algorithms is particularly adept at accurately solving complex scheduling problems. At the same time, its improved version is capable of handling a large number of states and solution spaces in a reasonable amount of time with guaranteed accuracy. After being statistically validated, the two-stage optimization method shows an insignificant deviation of 1–2 % (with an average of −0.91 %) from accurate results. However, the method significantly reduces computational time (with an average of 98.25 %), which improves decision-making accuracy and real-time feasibility. Decision makers can meet these elevated expectations by utilizing intelligent scheduling techniques, which exist alongside and complement past patterns.

Furthermore, with our model, decision makers can adjust parameters and weights to adapt to varying contexts based on the significance of different platform components in the operational scenario(The parameters in optimization objectives, weights of the three rules in Θ: Eq. (18), Eq. (21) and Eq. (22)). This method gives decision makers complete control over weight selection, allowing for expert perspective and necessary flexibility.

Finally, the research discusses a cross-platform linkage mechanism for distributing aircraft repair tasks. This mechanism is aimed at enhancing mission readiness and operational metrics by avoiding backlogs and reducing inefficiencies caused by concentrating maintenance on a single platform. Instead, repair tasks are allocated to platforms with lower maintenance loads, which results in better mission wave completion and overall readiness. While this mechanism offers several advantages, it may not always always produce optimal results due to its scheduling complexity. Overall, it is a valuable new effort for enhancing mission readiness, even though its scheduling complexity may lead to variations in results in certain scenarios.

7. Conclusion

To solve the integrated scheduling problem of the DP-ASMS, we first systematically analyzed the theoretical studies performed pertaining to aircraft task allocation and maintenance plans, sorties and recovery, maintenance and repair tasks, and dynamic scheduling in the civil and military aviation fields in the country and abroad. Second, a model with the WR, MR, and CR as the optimization objectives was established by considering various processes and constraints. Simultaneously, an integrated scheduling modeling that considered repair task transfer was performed. Subsequently, two optimization methods, i.e., the bi-level iteration optimization and two-stage optimization methods based on the surrogate function for fleet allocation on distributed platforms, were proposed, which can provide theoretical support for decision makers in formulating fleet allocation, sortie flight planning, and cooperative repair scheduling schemes for future maritime distributed operations. Finally, the following conclusions were inferred after performing a case study and analysis:

i. The established model can satisfy the constraints of various processes, resources, and time for distributed platform fleet allocation, flight timing planning, continuous cyclic sortie operation rules, and deck and maintenance operations. The Gantt chart of the scheduling results verified the accuracy of the modeling and the effectiveness of the optimization method.
ii. The proposed decoupling mechanism of the two-stage optimization method based on the surrogate function of fleet allocation on distributed platforms improved the sortie flight planning and maintenance scheduling efficiency while ensuring the scheduling optimization performance, as well as realized a reasonable and efficient scheduling scheme for fleet wave sorties and maintenance integration scheduling on a distributed platform.
iii. The cross-platform linkage mechanism was superior to the single-platform independent repair, based on all the indexes investigated in the modeling, particularly under conditions involving high task intensity, high fault probability, and frequent theoretical maintenance. Therefore, the cross-platform linkage mechanism can be attempted in future combat and training missions.

Several areas for future research can be identified. One point to consider is the modeling perspective. It is possible to explore more complex hypotheses, taking into account variables such as transfer time for maintenance personnel, interruptions in maintenance procedures, decision-making time for scheduling, and the costs of transferring maintenance tasks across platforms. These factors can be considered in the future to improve the overall maintenance process. Another important point to consider is the methodology perspective. For uncertain future distributed naval warfare scenarios, a feedback-driven, adaptive, proactive–reactive scheduling approach that uses deep reinforcement learning can better address dynamic disturbances. Simultaneously, with the emergence of technological developments in large-scale language models for the military, such as the Donovan system introduced by Scale AI in the United States, commanders have an opportunity to enhance their utilization of existing personnel for formulating innovative solutions. These advancements enable the evaluation of rapidly changing situations and the ability to comprehend, plan, and take action within minutes, signifying a crucial trajectory in future technological development.

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Changjiu Li: Writing – original draft. **Xichao Su:** Data curation. **Yong Zhang:** , Writing – review & editing. **Wei Han:** Funding acquisition. **Fang Guo:** Software. **Xuan Li:** Methodology. **Xinwei Wang:** Visualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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