



Research article

Multi-objective optimization of aviation equipment maintenance resource scheduling under high-disruption conditions based on an improved NSGA-II algorithm

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Abstract: Equipment maintenance-support resource scheduling under high-disruption conditions is critical to sustaining the operational readiness of essential equipment. The main challenge is coordinating maintenance-resource demand, scheduling time, and route reliability among sources of operating-environment uncertainty. To address this challenge, we developed a triangular-fuzzy-number-based multi-objective optimization model for equipment maintenance-support resource scheduling under high-disruption conditions. The model jointly minimized scheduling time, maximized route reliability, and minimized scheduling cost. To improve solution quality, an improved NSGA-II algorithm was developed by integrating a binary-real hybrid encoding scheme, adaptive genetic operators, and a constraint-penalty mechanism. The results indicated that the proposed model and algorithm enhanced the efficiency and robustness of maintenance-resource scheduling under high-disruption conditions and revealed the coupled trade-offs among scheduling time, route reliability, and scheduling cost under multiple uncertainties. This study provides a methodological basis and practical decision support for real-time aviation equipment maintenance scheduling in complex high-risk operating environments.

Keywords: equipment maintenance under high-disruption conditions; resource scheduling; triangular fuzzy number; multi-objective optimization; NSGA-II algorithm

Mathematics Subject Classification: 90B25, 90B36

1. Introduction

In information-intensive operations, effective scheduling of equipment maintenance-support resources is essential for sustaining the continuous operational capability of operating organizations. Scheduling efficiency directly determines how rapidly damaged equipment can be restored to operational readiness and can materially affect operation outcomes. Modern field operating environments are characterized by high dynamism, uncertainty, and complexity. Fluctuating operating intensity makes maintenance-support demand difficult to predict. External interference and abrupt meteorological changes introduce uncertainty into scheduling time, whereas road damage and field-route risks reduce transportation-route reliability. Traditional deterministic models often fail to capture these coupled operating-environment uncertainties and may therefore produce scheduling plans that deviate from operational conditions. Therefore, maintenance-resource scheduling under multiple uncertainties requires a model that balances rapid response, route resilience, and resource cost within a unified optimization framework. Research on equipment maintenance and logistics scheduling has progressed from single-objective to multi-objective optimization [1–4], from deterministic modeling to uncertainty-aware decision-making [5–6], and from conventional optimization methods to intelligent algorithms [7–9]. Studies on multi-objective optimization have provided useful methodological foundations. For instance, Zhou et al. developed an improved SPEA2 algorithm based on grid-density search and elite guidance, achieving efficient optimization of wastewater treatment operations and coordinated improvements in energy consumption and effluent quality [10]. Wang et al. proposed a resilient task-planning framework that combines task pre-allocation and reallocation modules to reduce the risks of UAV damage and task failure during coordinated operations; by integrating a probabilistically constrained multi-objective pre-allocation model with a rapid contract-net-based reallocation algorithm, the framework balanced task reliability with emergency-response efficiency [11]. Hezewijk et al. formulated a Markov decision process based on deep control learning, in which production-quantity decisions were decomposed into a sequence of subdecisions to reduce the action space; they addressed large-scale capacitated lot-sizing problems and yielded stronger scheduling policies under non-stationary demand than traditional heuristic and earlier deep reinforcement learning approaches [12]. Uncertainty-aware modeling has also developed rapidly. O’Neil et al. optimized predictive maintenance and task allocation under uncertainty to improve equipment operational readiness [13]. Chobar et al. established a robust mathematical model for specialized-equipment hub location and combined the model with metaheuristic algorithms to support multi-objective optimization in emergency logistics under uncertain conditions [14]. Liu et al. developed a chance-constrained, multi-skill resource-constrained scheduling model for large-platform hangar maintenance under batch-operation constraints; a hybrid particle swarm optimization algorithm and a rapid rescheduling strategy were designed to solve the model, and simulations showed greater flexibility and robustness than traditional algorithms [15]. Fuzzy theory is particularly useful for representing imprecise information in uncertain scheduling environments. Zhang et al. used trapezoidal fuzzy numbers to characterize uncertainty in the disassembly process and solved the resulting multi-objective optimization problem with a hybrid metaheuristic algorithm, enabling quantitative representation of cognitive uncertainty [16]. Tirkolaei et al. proposed an energy-saving scheduling model based on fuzzy mathematical programming and an adaptive artificial fish swarm algorithm, extending the application of fuzzy set theory in manufacturing systems [17]. In parallel, intelligent optimization algorithms have also continued to evolve. Jiao et al. proposed a joint

optimization method for equipment-group selective maintenance decisions and personnel allocation based on a non-homogeneous Markov model and an adaptive quantum immune algorithm, providing dynamic decision support for maximizing the overall probability of completing multiple tasks under limited resource constraints [18]. Yu proposed WOA-3, an improved whale optimization algorithm that enhances convergence and global search performance by optimizing three algorithmic stages. The application of WOA-3 to cloud-computing resource scheduling improves load balancing and resource utilization [19]. Despite this progress, three limitations remain in existing studies, as shown in Table 1.

Table 1. Comparison of scheduling methods.

Method	Content	Limitations
A maintenance task scheduling method based on an improved Max-Min ant colony optimization algorithm [20]	A dynamic scheduling model is developed for equipment maintenance tasks under high-disruption conditions with temporal uncertainty. The model maximizes the total importance of equipment awaiting repair and optimizes maintenance-task execution paths and scheduling plans.	This approach considers uncertainty only in the time dimension and does not account for coupling among multiple uncertain factors.
A multi-objective scheduling optimization method for high-disruption conditions based on AHP and linear weighting [21]	Interval numbers are used to characterize uncertainty, and a multi-objective optimization model for critical-material scheduling under high-disruption conditions is established to minimize cost and delay while maximizing delivery probability.	The model does not distinguish the differentiated support requirements of high-priority and standard-priority operating units.
A multi-agent collaborative scheduling method based on deep reinforcement learning [22]	A multi-agent coordination and scheduling system is developed for the field-service workflow to support task allocation and collaborative scheduling among sensing, decision-making, execution, and logistics agents.	The algorithmic network architecture is complex and involves high training and inference costs, which limits its applicability to urgent large-scale maintenance-scheduling decisions.

To address these gaps, we investigate optimization methods for resource scheduling in aviation-equipment maintenance under high-disruption conditions. Triangular fuzzy numbers are introduced to quantify uncertainties in resource demand, scheduling time, and path reliability. A multi-objective optimization model is constructed to minimize scheduling time, maximize path reliability, and minimize scheduling cost. An improved NSGA-II algorithm is designed with binary-real mixed encoding, adaptive genetic operators, and a constraint-penalty mechanism to improve solution accuracy and convergence performance under mixed decision variables and strong constraints. Simulation experiments evaluate the ability of the proposed model and algorithm to address uncertainty and multi-objective trade-offs, thereby providing decision support for maintenance support under high-disruption conditions.

2. Model description

2.1. Problem analysis

The scheduling of equipment maintenance and support resources under high-disruption conditions is a constrained decision-making problem in regional operations [23]. As shown in Figure 1, the central resource center transports maintenance resources to field demand points to satisfy urgent repair requirements for damaged equipment. The main difficulty lies in uncertainties in maintenance-resource demand, dispatch time, and route reliability. These parameters are difficult to describe with precise values because operating intensity, external interference, weather changes, road damage, and field-route risks change dynamically. Triangular fuzzy numbers are therefore used to quantify these uncertain parameters. The scheduling process also involves mutually competing objectives. Shorter dispatch times may reduce path reliability, whereas higher route reliability often increases scheduling costs. Cost control may further constrain response speed and route resilience. A feasible scheduling scheme must balance these objectives while satisfying resource availability, priority-based demand satisfaction, and minimum path reliability constraints. Accordingly, maintenance-resource scheduling under high-disruption conditions can be formulated as a strongly constrained fuzzy multi-objective optimization problem that requires models and algorithms that can jointly coordinate uncertainty, conflicting objectives, and operational constraints.

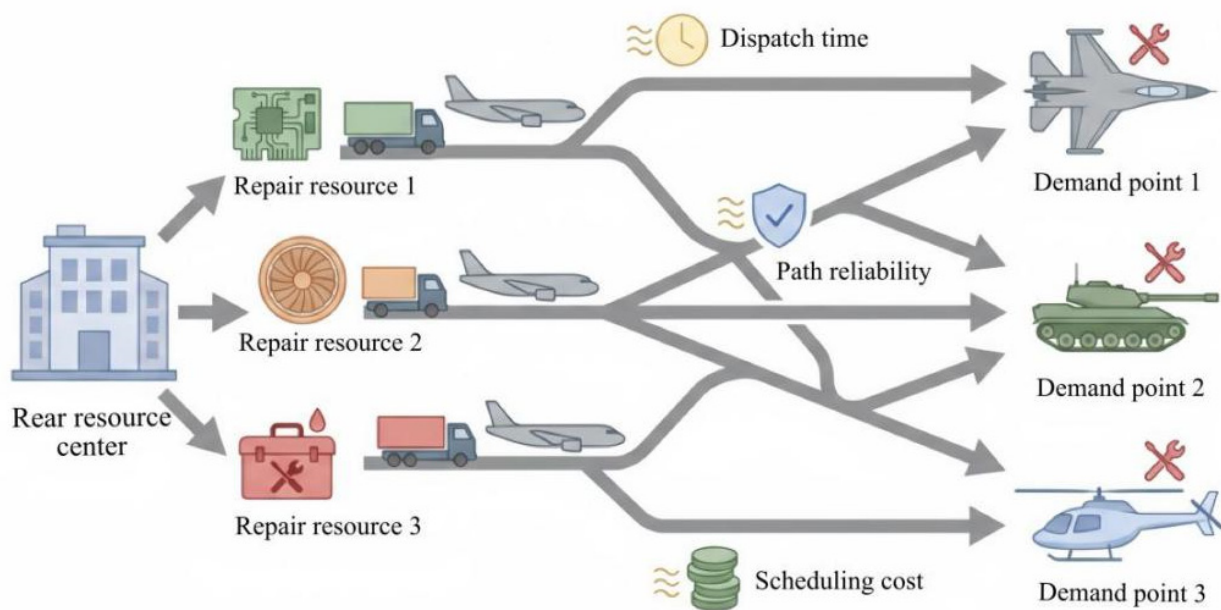


Figure 1. Schematic diagram of resource allocation for aircraft maintenance under high-disruption conditions.

2.2. Technical approach and assumptions

The technical procedure of the model for aviation-equipment maintenance-resource scheduling under high-disruption conditions is as follows:

Step 1: Define the uncertain parameters of the resource scheduling problem under high-disruption conditions. Triangular fuzzy numbers are used to consistently describe resource demand, scheduling time, and path reliability. Basic parameter sets, including the central resource center, demand points, and transportation routes, are established together with constraints on total resource availability, differentiated demand satisfaction, path reliability, vehicle loading capacity, and scheduling logic.

Step 2: Establish a multi-objective optimization model that jointly minimizes scheduling time, maximizes overall route reliability, and minimizes scheduling cost. The model includes constraints on total resource availability, differentiated fulfillment rates for core and non-core demand points, route reliability thresholds, vehicle loading capacity, and route-selection uniqueness.

Step 3: Design an improved NSGA-II algorithm with a binary-real mixed encoding strategy to jointly represent path selection and demand satisfaction rates. A penalized fitness function is introduced to coordinate multi-objective optimization with constraint satisfaction. A congestion-based adaptive crossover operator and a path-reliability-guided differential mutation operator are used to balance exploration and exploitation in the evolutionary search.

Step 4: The improved NSGA-II algorithm is implemented in PyCharm to solve the model and obtain the Pareto-optimal front. The optimal resource-allocation scheme and the coupled relationships among scheduling time, path reliability, and scheduling cost are then analyzed. Comparative experiments between deterministic and fuzzy models and among improved NSGA-II, standard NSGA-II, SPEA2, GA-TS, and UNSGA-III are conducted to evaluate convergence speed, solution-set uniformity, hypervolume, and constraint-violation probability.

The fundamental assumptions of the model are as follows:

(1) The total quantity of resources at the central maintenance-resource center remains constant throughout the scheduling cycle, with no additional supply or loss.

(2) Only direct transportation from the central resource center to the demand points is modeled. Split transportation through multiple routes and intermediate transshipment is excluded.

(3) Only the unit resource-scheduling cost during transportation is considered. Additional costs, including warehousing, loading and unloading, labor, management, and maintenance operations, are not included.

3. Model formulation

3.1. Nomenclature

To clarify the model formulation, the symbols used in this study are defined in Table 2.

Table 2. Symbol definitions.

Symbol	Definition
$R = \{r_1, r_2, \dots, r_m\}$	Set of resource types. r_k represents the k th type of maintenance resource, and m is the total number of resource types.
$D = \{d_1, d_2, \dots, d_n\}$	The set of demand points. d_j denotes the j th equipment demand point, and n is the number of demand points.
$P = \{p_1, p_2, \dots, p_t\}$	Set of routes. Transportation routes from the central resource center to the demand points.
O	Central resource center
Q_k	Total available resources. Maximum available quantity of the k th type of resource.
L_k	Vehicle load capacity. Maximum loading capacity per trip of the vehicle transporting the k th type of resource.
$\widetilde{D}_{jk}$	Fuzzy demand quantity of demand point d_j for the k th type of resource.
$\widetilde{T}_t$	Fuzzy transportation time of resources along route p_t
$\widetilde{K}_t$	Fuzzy path reliability of resources along route p_t
$\widetilde{C}_t$	Fuzzy unit transportation cost along route p_t
$\text{Defuzz}(\cdot)$	Defuzzification using the centroid method for triangular fuzzy numbers
f_1	Total dispatch time
f_2	Total path reliability
f_3	Total scheduling cost
β_j	Priority coefficient
α	Satisfaction threshold
γ	Minimum threshold for path reliability
$x_{jkt} \in \{0, 1\}$	Transportation of k th type of resource to demand point j via route p_t
$s_{jk} = [0, 1]$	Demand satisfaction rate of demand point d_j for the k th type of resource.

3.2. Uncertainty modeling and triangular fuzzy number representation

Triangular fuzzy numbers provide a practical tool for quantifying uncertainty. In the interval format of “minimum possible value–most likely value–maximum possible value,” they can represent fuzzy information in equipment maintenance under high-disruption conditions scheduling. Let $\widetilde{A} = (a^-, a^0, a^+)$ denote the set, where a^- is the minimum possible value, a^0 is the most likely value, and a^+ is the maximum possible value. The membership function is defined as follows:

$$\mu_{\widetilde{A}} = \begin{cases} 0, & x < a^- \\ \frac{x - a^-}{a^0 - a^-}, & a^- < x < a^0 \\ \frac{a^+ - x}{a^+ - a^0}, & a^0 < x < a^+ \\ 0, & x > a^+ \end{cases} \quad (3.1)$$

To support effective operations with fuzzy parameters in optimization models, we define the multiplication rule for triangular fuzzy numbers based on the extension principle of interval arithmetic. Let $\tilde{A} = (a^-, a^0, a^+)$ and $\tilde{B} = (b^-, b^0, b^+)$ be two non-negative triangular fuzzy numbers; their product is defined as $\tilde{A} \times \tilde{B} = (a^-b^-, a^0b^0, a^+b^+)$. Specifically, when $\rho \geq 0$ is a non-negative real constant, the multiplication of a constant and a triangular fuzzy number is defined as $\rho \times \tilde{A} = (\rho a^-, \rho a^0, \rho a^+)$. This operation preserves parameter uncertainty intervals and can be applied to fuzzy product terms in the model, such as reliability and demand or cost and demand, ensuring consistency in model derivation under fuzzy conditions.

In this study, we introduce triangular fuzzy numbers to account for uncertainties in maintenance-support resource demand under high-disruption conditions, scheduling time, path reliability, and unit scheduling cost, thereby establishing a tractable scheduling model. The demand for Type k resources at demand point d_j can be expressed as $\tilde{D}_{jk} = (d_{jk}^-, d_{jk}^0, d_{jk}^+)$; the time taken for a resource to travel along path p_t can be expressed as $\tilde{T}_t = (t_t^-, t_t^0, t_t^+)$; the path reliability of a resource via path p_t can be expressed as $\tilde{K}_t = (k_t^-, k_t^0, k_t^+)$; and the unit transportation cost for route p_t is $\tilde{C}_t = (c_t^-, c_t^0, c_t^+)$. To obtain deterministic values for computation, we adopt the centroid method to defuzzify triangular fuzzy numbers. The defuzzification operator is uniformly defined as follows:

$$\text{Defuzz}(\tilde{A}) = \frac{a^- + 2a^0 + a^+}{4}. \quad (3.2)$$

The centroid method represents fuzzy information by calculating the center of the region bounded by the membership function of a fuzzy number. This calculation characterizes the overall distribution of a triangular fuzzy number while retaining computational simplicity. Through this process, fuzzy operating-environment parameters can be converted into deterministic values to support real-time high-disruption decision-making, thereby providing a numerical basis for multi-objective optimization models. The centroid method nevertheless remains a deterministic simplification of fuzzy information. Although this method does not explicitly retain the interval width of a fuzzy number, namely the degree of uncertainty, the resulting value still integrates the characteristics of the lower, modal, and upper cases. Therefore, the centroid value can provide an engineering reference for scheduling decisions while preserving computational efficiency and model solvability. In the proposed model, risk-mitigation mechanisms are further embedded through path-reliability thresholds and differentiated demand-satisfaction rates, which partly offset the potential information loss caused by fuzzy number simplification. Moreover, the deterministic outputs of the centroid method can be directly integrated into existing multi-objective optimization algorithms and translated into clear, executable decision schemes for decision-support systems. Nevertheless, the centroid method remains limited when characterizing extreme fluctuation scenarios. In future studies, researchers may incorporate robust optimization or chance-constrained programming to enhance the adaptability of the model in highly uncertain environments.

3.3. Objective functions

3.3.1. Minimization of total dispatch time

The timeliness of equipment maintenance directly affects the regeneration of operational capability. Therefore, the total dispatch time required to transport maintenance resources from the origin to the demand points should be minimized. The total dispatch time is defined as the sum of the products of route transportation time and the corresponding path-selection variable, as follows:

$$\min f_1 = \sum_{j \in D, k \in R, t=1}^T \text{Defuzz}(\tilde{T}_t) \times x_{jkt}. \quad (3.3)$$

3.3.2. Maximization of overall path reliability

Under high-disruption conditions, transportation routes may be disrupted by field operating conditions and external interference, which may prevent maintenance resources from arriving on time. To improve scheduling-scheme resilience, we maximize the demand-weighted average route reliability. This objective assigns greater weight to scheduling tasks with larger resource demands and therefore more closely reflects the practical priorities of maintenance support under high-disruption conditions, as follows:

$$\max f_2 = \frac{\sum_{j=1}^n \sum_{k=1}^m \sum_{t=1}^T x_{jkt} \cdot d_{jk} \cdot \text{Defuzz}(\tilde{K}_t)}{\sum_{j=1}^n \sum_{k=1}^m d_{jk}}. \quad (3.4)$$

3.3.3. Minimization of total dispatch cost

While satisfying operational requirements, resource scheduling cost should be controlled to avoid excessive consumption of logistics resources. The total scheduling cost is defined as the sum of the products of route unit cost, resource demand, and the path-selection variable, as follows:

$$\min f_3 = \sum_{j \in D, k \in R, t=1}^T \text{Defuzz}(\tilde{C}_t) \times \text{Defuzz}(\tilde{D}_{jk}) \times x_{jkt}. \quad (3.5)$$

3.4. Decision variables

$x_{jkt} \in \{0,1\}$: If Type k resources are transported from the central maintenance base to demand point j via route p_t , then $x_{jkt} = 1$; otherwise, $x_{jkt} = 0$.

$s_{jk} = [0,1]$: The fulfillment rate of demand point d_j for Type k resources measures the adequacy of resource allocation. This variable is not calculated directly from an analytical formula; instead, it is determined through optimization during the solution process of the improved NSGA-II algorithm. Specifically, s_{jk} corresponds to the real-number-coded segment in the chromosome and is a continuous decision variable. At the initial algorithm stage, it is randomly generated within the feasible interval $[0.8,1]$ and subsequently evolves toward optimal values through selection, crossover, and Gaussian mutation. During the evolutionary process, the value of s_{jk} must satisfy the demand

satisfaction constraints. For core demand points, s_{jk} must reach 1; for non-core demand points, subject to the constraints of the encoding interval $[0.8,1]$, s_{jk} must not fall below the threshold α . Additionally, after each mutation operation, boundary pruning is applied to restrict the solution to interval $[0.8,1]$ and ensure feasibility. Ultimately, each Pareto-dominant solution corresponds to a specific set of demand-satisfaction rates.

3.5. Constraints

3.5.1. Total resource constraints

The total allocation of all resource types must not exceed the total available capacity of the central base, thereby ensuring resource-allocation feasibility:

$$\sum_{j \in D, t=1} \widetilde{D}_{jk} \times x_{jkt} \leq Q_k, \forall_k \in R. \quad (3.6)$$

3.5.2. Constraints on demand satisfaction

Differentiated supply-fulfillment rates are specified for demand points with different priorities: The supply-fulfillment rate for high-priority operating units (such as primary operating sites) must reach 100%, whereas that for non-core units may be appropriately reduced but must not fall below threshold α . Here, $\alpha = 80\%$, meaning that the satisfaction rate for non-core units should be no less than 80%. This value balances the priority of supporting high-priority operating units with the basic needs of non-core units, based on relevant emergency-logistics literature on threshold settings for support satisfaction rates [24,25], and is consistent with engineering practice.

$$s_{jk} \times \widetilde{D}_{jk} \geq \beta_j \times d_{jk}^0, \forall_k \in D, k \in R. \quad (3.7)$$

where β_j represents the priority coefficient for demand point j (core point $\beta_j = 1$, non-core point $\beta_j = 0$).

3.5.3. Path reliability constraints

To reduce scheduling failures caused by route interruption, the reliability of each selected route must exceed the threshold gamma:

$$\text{Defuzz}(\widetilde{K}_t) \geq \gamma, \forall_j \in D, k \in R, t=1, x_{jkt} = 1. \quad (3.8)$$

3.5.4. Vehicle loading capacity constraints

To simplify model solution, each resource type is assumed to be transported once. The maximum single-trip loading capacity of a transport vehicle must therefore be no less than the product of resource demand and the path-selection variable, ensuring that one transport trip can satisfy the corresponding demand:

$$L_k \geq \widetilde{D}_{jk} \times x_{jkt}, \forall_j \in D, k \in R, t = 1 \sim T. \quad (3.9)$$

3.5.5. Scheduling logic constraints

For each resource type at each demand point, only one transportation route is selected to ensure route-selection uniqueness:

$$\sum_{t=1}^T x_{jkt} = 1, \forall_j \in D, k \in R. \quad (3.10)$$

4. Problem solving based on the improved NSGA-II algorithm

To address insufficient solution robustness and elevated constraint-violation risk in standard NSGA-II when solving aviation-equipment maintenance-resource scheduling under high-disruption conditions problems with multiple uncertainties, we adopt an improved NSGA-II algorithm. The major enhancements include a binary-real mixed encoding scheme that represents path selection and resource allocation, a penalized fitness function that coordinates multiple objectives and explicitly handles constraints, an adaptive crossover operator based on congestion, and a differentiated mutation operator guided by path reliability. These strategies dynamically balance global search and local exploration while enhancing solution robustness. The core algorithmic parameters are listed in Table 3.

Table 3. Primary algorithmic parameters.

Parameter symbol	Default value
N	150
G	100
λ	100
Pc_max	0.8
Pc_min	0.4
Pm	0.2
σ	0.05
R_{low}	0.6
R_{mid}	0.8
R_{high}	0.9
δ_R	0.02

Step 1: Parameter initialization and population generation

The key algorithm parameters are first initialized. A chromosome design method based on binary-real mixed encoding is then employed to optimize the resource scheduling problem for equipment maintenance and support under high-disruption conditions. This encoding scheme divides each chromosome into two segments, with a total length of $2 * n * m$. The $n * m$ -bit binary segment represents resource path selection $x_{jkt} \in \{0, 1\}$, indicating whether resource type k at demand point j is transported via path t (1 indicates selection of this path, and 0 indicates non-selection). The

$n * m$ -bit real-number segment describes the demand fulfillment rate ($s_{jk} = [0,1]$), representing the demand satisfaction rate of demand point j for resource type k .

Step 2: Fitness function

To coordinate multi-objective optimization with constraint satisfaction, we introduce a penalty term into the fitness function. The function evaluates the overall performance of each individual and combines weighted summation with a penalty mechanism to coordinate objective values and constraint violations. The fitness function is expressed in minimization form, where a smaller value of F indicates better overall individual performance, as follows:

$$F = \omega_1 * f_1 + \omega_2 * (-f_2) + \omega_3 * f_3 + \lambda * Penalty. \quad (4.1)$$

where ω_1 , ω_2 , and ω_3 are the weights of the objective function; λ is the penalty coefficient; $Penalty$ is the penalty term for constraint violations; $Penalty = \sum_{c=1}^6 \max(0, g_c)$, where g_c represents the degree of violation of the c constraint; when the constraint is satisfied, $g_c \leq 0$, the penalty term is 0; and when the constraint is violated, $g_c > 0$.

Step 3: Non-dominated sorting and crowding-distance calculation

After fitness evaluation, the population is sorted by non-dominance, and the crowding distance is calculated. Individuals are first ranked according to Pareto dominance. If an individual is no worse than another individual across all objective functions and better in at least one objective, the former dominates the latter. All non-dominated individuals are assigned to the first front. These individuals are then temporarily removed, and the next non-dominated front is identified from the remaining population. This process continues until all individuals have been assigned to a front. The crowding distance is then calculated within each front to maintain diversity in the objective space. A larger crowding distance indicates that neighboring solutions are more sparsely distributed, so the corresponding individual is preferentially retained during subsequent selection. The non-dominated rank and crowding distance jointly determine the priority of each individual in elite selection.

Step 4: Elite retention and environmental selection

The elite retention strategy preserves convergence and diversity during evolution. In each generation, the parent and offspring populations generated through crossover and mutation are merged into a temporary population. Fast non-dominated sorting is then applied to determine the Pareto-front rank of each individual, and the crowding distance within each front is calculated to measure solution sparsity in the objective space. Following the rule of first prioritizing non-dominated ranks and then comparing crowding distances, a number of individuals equal to the initial population size is selected to form the next generation. Individuals with better front ranks are retained first. When only part of a front can be retained, individuals with larger crowding distances are selected. This strategy retains high-quality individuals while maintaining a diverse Pareto front.

Step 5: Crossover operation

To balance global search with local optimization dynamically, we employ an adaptive crossover probability adjustment strategy based on congestion. First, the mean crowding level $\bar{d}$ of all individuals in the population is calculated. For any two parent individuals a and b to be crossed, d_a and d_b represent the crowding levels of a and b , respectively, and their average crowding level is

$$d_{avg} = \frac{d_a + d_b}{2} \quad \text{The formula for calculating the crossover probability is:}$$

$$p_c = f(x) = \begin{cases} 0.8 & , d_{\text{avg}} > \bar{d} \\ 0.4 & , d_{\text{avg}} \leq \bar{d} \end{cases} \quad (4.2)$$

When the average crowding of an individual exceeds the population mean, it indicates that the solution in that region exhibits greater diversity; therefore, a higher crossover probability P_{c_max} is used to expand the search space further. When the average crowding is less than or equal to the population mean, the solution region is more convergent; therefore, a lower crossover probability P_{c_min} is used to accelerate population convergence toward high-quality solutions and prevent premature convergence caused by excessive crossover. To coordinate path selection and resource allocation in the scheduling problem, crossover operations employ a segmented gene exchange strategy: Let the chromosome consist of the path selection gene $X = [x_{jkt}]$ and the demand satisfaction gene $S = s_{jk}$. A crossover point $pos (1 \leq pos \leq 2 * n * m)$ is randomly selected on the chromosome, and the gene segments to the right of the crossover point are exchanged, that is:

$$\begin{cases} child_a[pos+1:end] = parent_b[pos+1:end] \\ child_b[pos+1:end] = parent_a[pos+1:end] \end{cases} \quad (4.3)$$

where $child_a$ and $child_b$ represent the two daughter chromosomes generated by crossover, while $parent_a$ and $parent_b$ represent the parent chromosomes. Moreover, boundary constraints are applied to the demand satisfaction rate gene to ensure that it remains within a reasonable range.

$$s'_{jk} = clip(s'_{jk}, 0.8, 1.0), \quad s''_{jk} = clip(s''_{jk}, 0.8, 1.0). \quad (4.4)$$

Step 6: Mutation operation

The mutation operator is a key mechanism for maintaining population diversity and enhancing solution robustness while accommodating the constraints inherent in equipment maintenance under high-disruption conditions-support resource scheduling. Differentiated mutation strategies are designed for different gene segments to improve solution robustness and optimization efficiency. For gene x_{jkt} , which represents binary path selection, bit mutation is employed together with path-reliability constraints to guide directed optimization. For gene positions corresponding to defuzzified path reliability level $\text{Defuzz}(\tilde{K}_t) < R_{low}$, forced mutation inversion is performed, i.e., $x'_{jkt} = 1 - x_{jkt}$: After mutation, these genes are simultaneously mapped to the high-reliability path ($\text{Defuzz}(\tilde{K}_t) \geq R_{high}$) gene corresponding to the same demand point, thereby improving path robustness; for paths with medium reliability level ($R_{low} \leq \text{Defuzz}(\tilde{K}_t) < R_{mid}$), random mutation is applied at a fixed mutation probability P_m to maintain population diversity while avoiding excessive perturbation; and fine-tuning within a local interval is permitted only when the path reliability defuzzified value exceeds R_{high} and the reliability difference between adjacent paths is less than the δ_R value, ensuring the stability of high-quality solutions. For real-valued gene segments (demand fulfillment rate), the Gaussian mutation method is adopted, with the mutation formula $s'_{jk} = \max(0.8, \min(1, s_{jk} + N(0, 0.05^2)))$, where $N(0, 0.05^2)$ is a Gaussian random variable with a mean of 0 and a standard deviation of 0.05. Through small-scale random perturbations, boundary

constraints ensure that the mutated values always remain within the [0.8, 1] interval, thereby improving resource-allocation accuracy while satisfying the demand-satisfaction-rate constraint.

Step 7: Termination check and output

After crossover and mutation operations, a new offspring population is generated. The algorithm then determines whether the evolutionary generation has reached the maximum number of iterations, Tmax. If the termination condition is not met, the algorithm returns to Step 2 for the next evolutionary cycle. Otherwise, the iteration stops. All individuals in the final generation with a non-dominated rank of 1 are output as the Pareto-optimal solution set, providing decision-makers with scheduling schemes that reflect the best trade-offs among conflicting objectives.

The flowchart of the improved NSGA-II algorithm is shown in Figure 2.

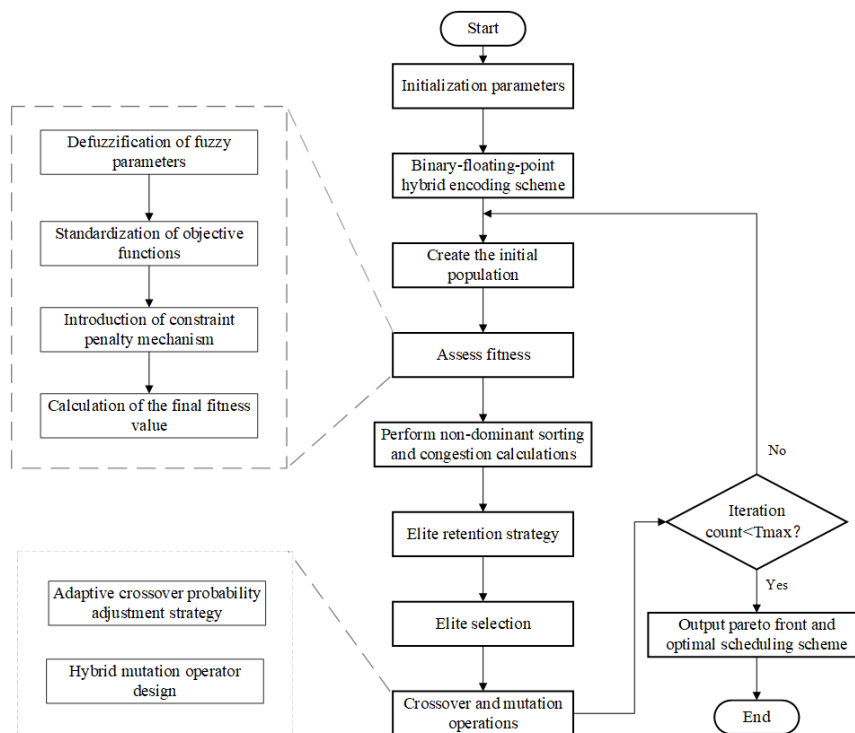


Figure 2. Flowchart of the improved NSGA-II algorithm.

4.1. Evaluation indicators

(1) Robustness index (RI)

The robustness index is used to measure the degree of deviation in the objective function value of a scheduling scheme when it faces random parameter fluctuations. A smaller deviation indicates a stronger ability to accommodate uncertainty. For the i th objective function, the formula for calculating the RI_i th robustness metric is:

$$RI_i = \frac{1}{K} \sum_{k=1}^K \frac{|f_{i,k}^{actual} - f_i^{pred}|}{|f_i^{pred}| + \varepsilon} \cdot f_i^{pred} \quad (4.5)$$

where K represents the total number of Monte Carlo sampling trials; f_i^{pred} represents the theoretical predicted value of the i th objective output during model optimization; $f_{i,k}^{actual}$ represents the simulated actual objective value calculated based on the simulated parameters obtained from the k th random sample; and ε is a small constant (set to 10^{-6}) used to prevent the denominator from becoming zero.

To assess comprehensively the overall stability of multi-objective optimization solutions, the Comprehensive Robustness Index (CRI) is defined as the average of the RI_i values for each objective:

$$CRI = \frac{1}{M} \sum_{i=1}^M RI_i. \quad (4.6)$$

where M represents the total number of objective functions

(2) Constraint violation rate (CVR)

In resource scheduling under high-disruption conditions, exceeding resource limits or failing to satisfy critical requirements may lead to serious operational consequences. The CVR evaluates the probability that a solution violates at least one constraint under random parameter fluctuations. The formula is as follows:

$$CVR = \frac{1}{K} \sum_{k=1}^K I_k. \quad (4.7)$$

where I_k is the indicator function. If, during the k th simulation sample evaluation, the solution violates any constraint, then $I_k = 1$; if all constraints are satisfied, then $I_k = 0$.

(3) Spacing metric

To evaluate the uniformity of the Pareto-solution distribution, the Spacing metric is adopted. A smaller Spacing value indicates a more uniform solution distribution in the objective space. The formula is as follows:

$$\text{Spacing} = \sqrt{\frac{1}{|F|-1} \sum_{x \in F} (d_x - \bar{d})^2}. \quad (4.8)$$

where F denotes the set of Pareto-optimal solutions, d_x is the minimum Euclidean distance from the solution to all other solutions on the frontier, and $\bar{d}$ is the average of all d_x values.

(4) Hypervolume indicator (HV)

To evaluate jointly the convergence and diversity of the Pareto solution set, we adopt the hypervolume (HV) indicator. A larger HV value indicates that the solution set covers a larger hypervolume in the objective space and therefore shows better overall convergence and diversity. The calculation formula is as follows:

$$HV(F) = \lambda(\cup_{f \in F} \{x \in \mathbb{R}^3 \mid f \prec x \prec r^*\}). \quad (4.9)$$

where F represents the set of Pareto-optimal solutions, r^* is the predefined reference point, $\lambda(\cdot)$ denotes the Lebesgue measure (i.e., the hypervolume of the enclosed region), and $f \prec x \prec r^*$ denotes the hyperrectangular region bounded by the solution f and the reference point r^* . We use the WFG recursive algorithm for precise computation, with the reference point set to $r^* = (1.1, 1.1, 1.1)$ in the normalized objective space to ensure that all non-dominated solutions lie within the range defined by the reference point.

5. Analysis of the case study

An operating environment operations center is used as the simulation scenario. The central resource center (O) is assumed to dispatch three types of maintenance resources to four demand points under high-disruption conditions. Demand points 1 and 2 are high-priority operating units, whereas demand points 3 and 4 are standard-priority operating units. Four direct transportation routes connect the central resource center with the demand points. The types and total quantities of maintenance resources at the central resource center are listed in Table 4. The resource types and quantities required at each demand point are listed in Table 5, and the single-trip transport time, path reliability, and unit transport cost of each route are given in Table 6.

Table 4. Types and quantities of maintenance resources at the central maintenance base (O).

Types of resources (r_k)	Total amount (Q_k)
Modular Avionics Components (units)	180
Engine Blades (pieces)	110
Aircraft Hydraulic System Repair Kit (set)	95

Table 5. Types and quantities of maintenance support resources required at demand points.

Types of Resources (r_k)	Requirement 1	Requirement 2	Requirement 3	Requirement 4
Modular Avionics Components (units)	25,32,42	28,38,45	18,28,35	22,32,40
Engine Blades (pieces)	18,28,35	15,25,32	12,20,28	10,16,22
Aircraft Hydraulic System Repair Kit (set)	15,25,32	12,20,28	22,32,40	15,25,32

Table 6. Single-trip transportation time, route reliability, and unit transportation cost for each route.

Path ID	Dispatch time $\tilde{T}_i$ (hours)	Path reliability $\tilde{K}_i$	Unit scheduling cost $\tilde{C}_i$ (thousand yuan)
P_1	1.5,2.0,3.0	0.75,0.85,0.95	1.2,1.5,1.8
P_2	2.0,2.5,4.0	0.65,0.75,0.85	0.8,1.0,1.2
P_3	3.0,4.0,5.0	0.80,0.90,1.00	1.5,1.8,2.0
P_4	2.5,3.5,5.5	0.55,0.65,0.75	0.5,0.6,0.8

To verify the effectiveness of the proposed algorithm for scheduling maintenance resources for specialized equipment, the PyCharm 2023.1 development environment is used on hardware configured with an Intel Core i9-12900H processor to model and solve the scheduling problem for aviation equipment maintenance resources. The objective is to minimize scheduling time, maximize path

reliability, and minimize scheduling cost. In the improved NSGA-II algorithm, population size N and the number of generations G are two core parameters. The constraint penalty coefficient λ substantially influences algorithm search behavior within the feasible region and convergence performance. The mutation operator of the improved algorithm also incorporates a differentiated mutation strategy based on path reliability, involving several key threshold parameters, including the low reliability threshold R_{low} , the medium reliability threshold R_{mid} , the high reliability threshold R_{high} , and the path reliability differentiation threshold δ_R . The values of these parameters directly affect path robustness and the ability of the algorithm to maintain population diversity. To this end, we employ the control variable method to conduct a sensitivity analysis on these parameters and determine their optimal values. First, a sensitivity analysis of the penalty coefficient λ is conducted using the classical value $\lambda \in \{50, 100, 150, 200\}$. Five independent random replicates are performed, and the mean values of the evaluation metrics are then analyzed statistically. The detailed results are shown in Table 7.

Table 7. Penalty coefficient comparison table.

λ	HV	Spacing	λ	HV	Spacing
50	0.7569	0.0285	150	0.8257	0.0295
100	0.8383	0.0275	200	0.8009	0.0305

As shown in Table 7, when the penalty coefficient is too low, the penalty is insufficient to effectively eliminate infeasible scheduling solutions, resulting in weaker algorithm convergence. When the penalty coefficient is too large, the excessive penalty suppresses population diversity, deteriorates the Spacing metric, reduced uniformity of the solution set distribution, and a significant decline in the HV value. When $\lambda = 100$, the algorithm achieves optimal overall performance, indicating that this value provides the best balance among constraint satisfaction, global convergence, and solution-set uniformity. Therefore, we select $\lambda = 100$ as the penalty coefficient. A univariate sensitivity analysis is then conducted on the low reliability threshold R_{low} , medium reliability threshold R_{mid} , high reliability threshold R_{high} , and path reliability difference threshold δ_R . Based on engineering experience, three representative values are selected for each parameter: R_{low} is set to 0.55, 0.60, and 0.65; R_{mid} is set to 0.75, 0.80, and 0.85; R_{high} is set to 0.85, 0.90, and 0.95; and δ_R is set to 0.01, 0.02, and 0.03. Five independent replicates are performed for each parameter set, and the mean values of the evaluation metrics are analyzed statistically. The results are shown in Table 8.

As shown in Table 8, for the low reliability threshold R_{low} , when the value is set to 0.60, the HV and Spacing metrics exhibit the best overall performance among the three tested values. If the threshold is too low, the constraint is insufficiently strong, and unreliable paths interfere with the quality of the solution set; if the threshold is too high, the feasible region shrinks, and the HV value decreases significantly. For the medium reliability threshold R_{mid} , when set to 0.80, the HV metric is highest, and the Spacing metric is lowest; the algorithm achieves the optimal balance between convergence and distribution uniformity. Deviations from 0.80 result either in overly broad intervals that blur path classification or in overly narrow intervals that restrict the search space. For the high reliability threshold R_{high} , when set to 0.90, the HV and Spacing metrics are optimal among the three. When the threshold is further increased to 0.95, path filtering becomes overly stringent and suppresses population diversity. For the path reliability difference threshold δ_R , when set to 0.02, the HV and Spacing metrics reach their optimal values, ensuring flexibility for local fine-tuning while limiting the effect of invalid

perturbations on algorithm stability. Therefore, R_{low} is set to 0.6, R_{mid} to 0.8, R_{high} to 0.9, and δ_R to 0.02. The population size N and the number of iterations G are two core algorithm parameters. We evaluate several representative combinations of N and G through five independent random runs and calculates the mean value of each evaluation metric. The results are shown in Table 9.

Table 8. Single-factor sensitivity analysis results for R_{low} , R_{mid} , R_{high} , and δ_R .

Parameter	Value	HV	Spacing	Parameter	Value	HV	Spacing
R_{low}	0.55	0.8182	0.0291	R_{high}	0.85	0.7903	0.0347
R_{low}	0.60	0.8640	0.0280	R_{high}	0.90	0.8497	0.0315
R_{low}	0.65	0.7971	0.0331	R_{high}	0.95	0.7829	0.0358
R_{mid}	0.75	0.8145	0.0356	δ_R	0.01	0.8097	0.0331
R_{mid}	0.80	0.8315	0.0287	δ_R	0.01	0.8320	0.0268
R_{mid}	0.85	0.8190	0.0315	δ_R	0.03	0.8120	0.0278

Table 9. Comparison results under different population sizes and numbers of iterations.

Set	N	G	HV	Spacing	Set	N	G	HV	Spacing
1	50	100	0.7294	0.0370	10	200	100	0.7871	0.0276
2	50	200	0.6828	0.0377	11	200	200	0.8084	0.0254
3	50	300	0.6504	0.0385	12	200	300	0.8476	0.0250
4	100	100	0.8567	0.0448	13	250	100	0.8292	0.0405
5	100	200	0.7689	0.0294	14	250	200	0.7880	0.0269
6	100	300	0.8176	0.0379	15	250	300	0.7855	0.0318
7	150	100	0.8216	0.0279	16	300	100	0.8110	0.0364
8	150	200	0.8472	0.0227	17	300	200	0.8372	0.0281
9	150	300	0.8172	0.0334	18	300	300	0.7854	0.0328

As shown in Table 9, when the population size is 150 and the number of iterations is 200, the HV value is 0.8472, which is the second highest among all parameter combinations, and algorithm convergence and solution-set coverage are close to optimal. The average Spacing value is 0.0227, which is the lowest among all combinations, indicating the most uniform distribution of solutions. Compared with combination 4, which has the highest HV value, this combination provides a clear Spacing advantage. Compared with combinations 11 and 12, which have similar Spacing values, this combination achieves a more competitive HV value. Overall, $N = 150$ and $G = 200$ provide a balanced parameter setting that balances convergence accuracy, solution-set uniformity, and computational cost. Excessively large parameter values substantially increase computational cost, whereas excessively small values cannot provide sufficient evolutionary depth. Therefore, we use $N = 150$ and $G = 200$ as the optimal parameter combination for the improved NSGA-II algorithm.

The upper bound $P_c_max = 0.8$, lower bound $P_c_min = 0.4$, and value of the mutation probability $P_m = 0.2$ are selected by referencing the parameter design approaches for adaptive genetic algorithms in relevant literature [26–28]. In these studies, adaptive crossover and mutation mechanisms are employed to improve algorithm performance for complex scheduling, dynamic programming, and cost optimization problems; the parameter-selection principles in these studies provide a reference for this

study. Considering the characteristics of the maintenance-resource scheduling problem under high-disruption conditions, this parameter set is selected to ensure algorithm stability and solution quality. The Gaussian mutation parameter with a standard deviation of 0.05 is selected based on Reference 29, which explicitly employs Gaussian mutation with a mutation rate of 0.05 and ensures parameter feasibility through boundary pruning. Experimental results have verified that this parameter setting balances effective perturbation with solution stability [29]. After selecting and validating the key parameters of the algorithm, the resource demands at each demand point and the transportation-metric expected values for each route are determined through calculation. Table 10 lists the expected values for the types and quantities of maintenance and support resources required at each demand point, while Table 11 lists the expected values for the single-trip transportation time, route reliability, and unit transportation cost for each route.

Table 10. Expected values of the types and quantities of maintenance support resources required at each demand point.

Types of Resources (r_k)	Requirement 1	Requirement 2	Requirement 3	Requirement 4
Modular Avionics Components (units)	32.75	37.25	27.25	31.5
Engine Blades (pieces)	27.25	24.25	20	16
Aircraft Hydraulic System Repair Kit (set)	24.25	20	31.25	24.25

Table 11. Expected values of single-trip transportation time, route reliability, and unit transportation cost for each route.

Path ID	Dispatch Time $\widetilde{T}_i$ (hours)	Path Reliability $\widetilde{K}_i$	Unit scheduling cost $\widetilde{C}_i$ (thousand yuan)
P_1	2.12	0.85	1.5
P_2	2.75	0.75	1
P_3	4	0.9	1.77
P_4	3.75	0.65	0.62

After iterative optimization, the Pareto-front solutions for maintenance resource allocation obtained by the improved NSGA-II algorithm are shown in Figure 3. The solution set is widely distributed across the three-dimensional objective space, indicating that the improved NSGA-II algorithm has strong global-search and convergence capabilities. The algorithm identifies a diverse set of non-dominated solutions and provides candidate solutions for multi-objective decision-making. The distribution across the three objective dimensions reveals clear trade-offs. Solutions with higher path reliability are generally associated with higher scheduling cost and moderate scheduling time, whereas low-cost solutions usually show lower path reliability. Solutions with moderate scheduling time tend to exhibit intermediate path reliability and cost. These patterns reveal a coupled trade-off among scheduling time, scheduling cost, and path reliability, which is consistent with the practical constraints and decision logic of maintenance-resource scheduling under high-disruption conditions.

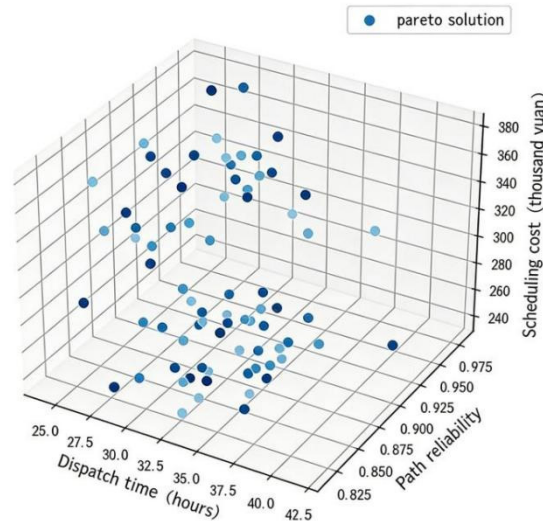


Figure 3. Pareto front obtained by the improved algorithm.

In multi-objective optimization problems, all solutions on the Pareto front are non-dominated. For practical decision-making, it is necessary to select a scheduling plan that best meets task requirements based on the urgency of the operating situation, task reliability requirements, and resource constraints. To this end, we conduct sensitivity analysis on the weight coefficients to quantitatively evaluate the trade-offs among the three objectives under different operational preferences. We select four typical weight combinations for analysis, corresponding to extreme operational scenarios (time-priority, reliability-priority, and cost-priority) and a general operational scenario that balances all three, thereby providing quantitative support for scheduling decisions under different field operating conditions. Specifically, ω_1 , ω_2 , and ω_3 correspond to the objective weights that minimize total scheduling time, maximize total path reliability, and minimize total scheduling cost, respectively. The analysis results are shown in Table 12.

Table 12. Analysis of different weight combinations.

Weight Combinations	Weights ($\omega_1, \omega_2, \omega_3$)	Scenario description	Total dispatch time (hours)	Total path reliability	Total scheduling cost (thousand yuan)
1	(0.8,0.1,0.1)	Time priority	25.50	0.84	335
2	(0.1,0.8,0.1)	Reliability priority	36.78	0.95	380
3	(0.1,0.1,0.8)	Cost priority	37.44	0.82	268
4	(0.4,0.3,0.3)	Balanced allocation	29.76	0.85	290

The results in Table 12 clarify the trade-offs among the three objectives. Under the time-priority weighting scheme, the algorithm obtains the shortest scheduling time of 25.50 h, whereas the scheduling cost increases to 335,000 yuan. Under the reliability-priority scheme, the algorithm achieves the highest path reliability, but the scheduling time increases to 36.78 h, and the total scheduling cost reaches 380,000 yuan. This result indicates that high resilience requires additional time and economic costs. Under the cost-priority scheme, the total scheduling cost decreases to 268,000 yuan, but the scheduling time increases to 37.44 h, and path reliability declines to the lowest level,

which may increase scheduling-failure risk. These results further indicate the trade-offs among timeliness, path reliability, and scheduling cost efficiency in maintenance-resource scheduling under high-disruption conditions.

We follow the core rationale of the subjective weighting method described in Reference 30 and adopt a classical a priori preference formulation used in multi-objective optimization. For multi-objective scheduling under high-disruption conditions, the weight configuration should align with operational requirements. By quantifying the relative importance of different objectives, this strategy aligns the optimization direction with task needs and provides theoretical support for the weight assignment used in this study [30]. The weight-setting rationale includes two major components: First, the weights reflect the operational characteristics of aviation-equipment maintenance support under high-disruption conditions, in which rapid restoration of operational readiness and return of equipment to service are essential for sustaining continuous operational capability. Second, the weighting scheme incorporates the expertise of domain scheduling specialists to balance the secondary objectives of route reliability and scheduling cost, consistent with the emergency-support logic of rapid response, route resilience, and cost control. The optimal decision for equipment maintenance and support under high-disruption conditions is therefore not determined by a single-objective extremum but a multi-objective Pareto optimum. We select a weight combination of 0.4, 0.3, and 0.3 for the objective function weights ω_1 , ω_2 , and ω_3 , respectively, and derive the optimal resource allocation scheme, as shown in Figure 4.

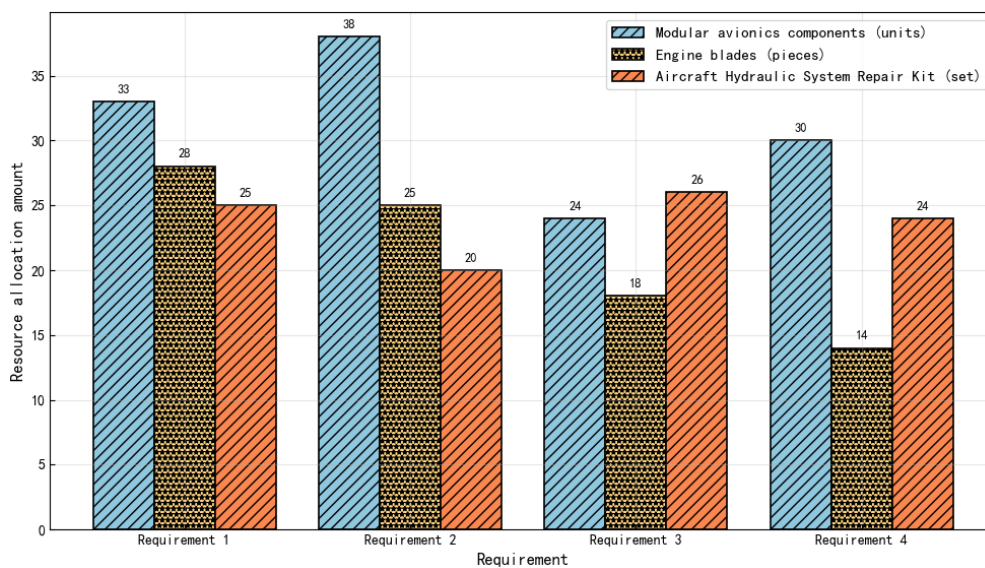


Figure 4. Optimal maintenance resource allocation diagram.

Under this setting, the total scheduling time is 29.76 h, the path reliability is 0.8575, and the total scheduling cost is 290,200 yuan. Demand points 1 and 2 are core demand points with a resource-allocation fulfillment rate of 100%. For non-core demand points 3 and 4, the resource-allocation fulfillment rate exceeds 80%.

5.1. Comparison of deterministic and fuzzy models

To further evaluate the effectiveness and necessity of the proposed fuzzy model in addressing multiple operating environment uncertainties, in this section, we compare the deterministic model with

the fuzzy model. The deterministic model performs scheduling optimization using only the most likely values of uncertain parameters and therefore ignores the fluctuation intervals. In contrast, the proposed fuzzy model incorporates the triangular fuzzy distributions of the parameters. To ensure a fair comparison, both models are solved using the improved NSGA-II algorithm with identical runtime parameters. Monte Carlo simulation with 100 random samples of triangular fuzzy numbers is used to represent parameter fluctuations in realistic high-risk operating environments. The Robustness Index (RI) and Constraint Violation Rate (CVR) are introduced to quantify robustness and safety under simulated parameter fluctuations. The robustness comparison is shown in Figure 5, and the constraint violation comparison is shown in Figure 6.

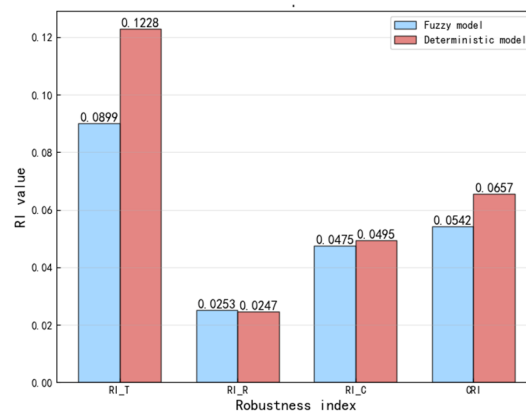


Figure 5. Comparison of Robustness Metrics.

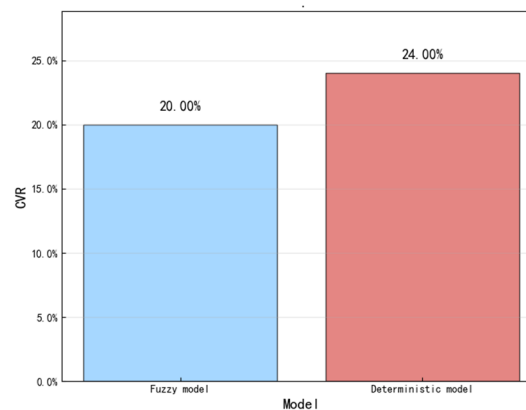


Figure 6. Comparison of Probabilities of Constraint Failure.

As shown in Figure 5, under identical algorithmic and parameter settings, the comprehensive robustness index (CRI) of the fuzzy model is 0.0542, which is lower than the value of 0.0657 obtained by the deterministic model. For specific objectives, the fuzzy model shows advantages in scheduling time robustness (RI_T) and scheduling cost robustness (RI_C), with deviations decreasing to 0.0899 and 0.0475, respectively. This result indicates that the deterministic model, by ignoring parameter fluctuation intervals, is more sensitive to environmental fluctuations affecting time and cost. By contrast, the fuzzy model absorbs part of the fluctuations through triangular fuzzy distributions. For path reliability robustness (RI_R), the two models perform similarly, and the deterministic model

shows only a slight numerical advantage, with a difference of 0.0006. This similarity is mainly attributable to the hard-threshold constraint on path reliability, which drives both models to select high-reliability routes. Overall, the fuzzy model shows better overall robustness.

As shown in Figure 6, the constraint violation rate (CVR) is 24.00% for the deterministic model and 20.00% for the fuzzy model. In practical emergency scheduling, exceeding resource limits or failing to satisfy core requirements can have serious consequences. The deterministic model tends to drive resource use toward boundary values to obtain an apparently optimal objective value, making the solution vulnerable to hard-constraint violations when actual demand exceeds the most likely value. By contrast, the fuzzy model preserves buffer space for parameter fluctuations during optimization and therefore exhibits greater fault tolerance under random disturbances. This behavior improves the safety and reliability of emergency scheduling.

Overall, under equivalent algorithmic conditions, the fuzzy model shows distinct advantages in highly uncertain high-disruption environments. Compared with the deterministic model, the fuzzy model improves solution stability and constraint-satisfaction performance, supporting the need to incorporate fuzzy uncertainty into high-risk resource-scheduling models.

5.2. Algorithm comparison

To evaluate the effectiveness of the improved NSGA-II algorithm, we conduct comparative experiments using a controlled-variable strategy. The comparison algorithms include the standard multi-objective optimization algorithms NSGA-II and SPEA2, the hybrid metaheuristic GA-TS, and the high-dimensional multi-objective optimization algorithm UNSGA-III. To ensure fairness, all algorithms use the same initial-population generation strategy and random seed, so that each algorithm starts from the same initial population. The comparison assesses algorithm performance from two aspects: dynamic optimization processes and static optimization results.

5.2.1. Dynamic performance comparison

(1) Comparison of fitness value convergence curves

Fitness convergence describes the process by which the best population fitness decreases and gradually stabilizes during iteration. A smaller fitness value indicates better overall solution quality. Figure 7 compares the convergence curves of the five algorithms.

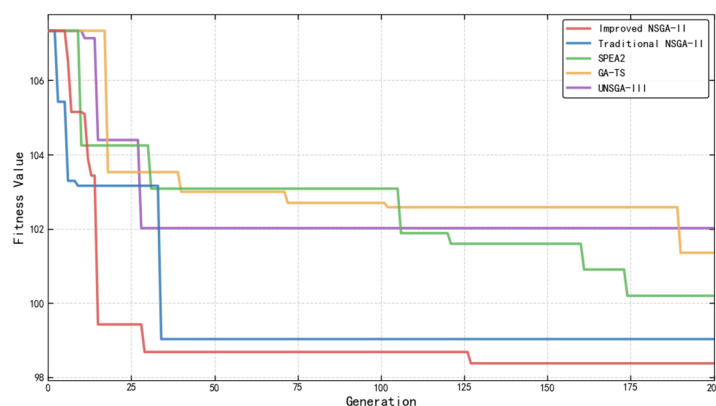


Figure 7. Comparison of fitness value convergence curves.

As shown in Figure 7, the five algorithms exhibit differences in convergence behavior and optimization performance. Traditional NSGA-II lags behind the improved algorithm in convergence speed and solution accuracy, indicating that the improvement strategy enhances optimization performance. UNSGA-III converges rapidly in the early stages but enters an optimization plateau during the middle iterations, showing a tendency toward premature convergence and limited ability to escape local optima. The convergence curve of SPEA2 shows a step-like decline; its convergence rate is relatively slow, making it difficult to obtain efficient solutions under limited iteration resources. The convergence curve of GA-TS exhibits a step-like decline, with a slow optimization pace and limited solution accuracy, resulting in overall weak optimization performance. In contrast, the improved NSGA-II algorithm starts with the lowest initial fitness among all algorithms and maintains a continuous, stable downward trend throughout the iteration cycle, with no obvious convergence-stagnation phase. It continuously explores the solution space for better solutions and converges to the global minimum fitness value. This demonstrates stronger global-search capability, a greater ability to escape local optima, a smoother convergence process, and higher optimization accuracy, thereby validating the effectiveness of the proposed improved NSGA-II algorithm.

(2) Comparison of uniformity

To evaluate the uniformity of the Pareto-solution distribution, the Spacing metric is used. Table 13 compares the Spacing values of the five algorithms.

Table 13. Spacing value versus number of generations.

Generation	0	50	100	150	200
Improved NSGA-II	0.0693	0.0604	0.0434	0.0405	0.0371
Traditional NSGA-II	0.0693	0.0508	0.0501	0.0479	0.0470
SPEA2	0.0693	0.0568	0.0594	0.0526	0.0567
GA-TS	0.0693	0.0482	0.0509	0.0486	0.0466
UNSGA-III	0.0693	0.0533	0.0435	0.0485	0.0397

As shown in Table 13, the algorithms differ substantially in solution distribution uniformity across iteration stages. The Spacing value of the improved NSGA-II exhibits a continuous and monotonically decreasing trend throughout the iteration process, and its value remains better in the middle and late stages, indicating that its solution-distribution uniformity is consistently superior to that of other algorithms. Traditional NSGA-II shows an overall downward trend but lags behind the improved NSGA-II. The Spacing values for GA-TS and UNSGA-III rebound during iteration, suggesting a decline in population diversity; the Spacing value for SPEA2 fluctuates significantly, indicating insufficient stability. Overall, the improved NSGA-II performs best in terms of solution-distribution uniformity, further validating the effectiveness of the proposed improvement strategy.

(3) Comprehensive comparison of convergence and diversity

To comprehensively evaluate the convergence and diversity of the solution sets obtained by the multi-objective optimization algorithms, the hypervolume (HV) indicator is adopted. Figure 8 compares the HV values of the five algorithms over generations.

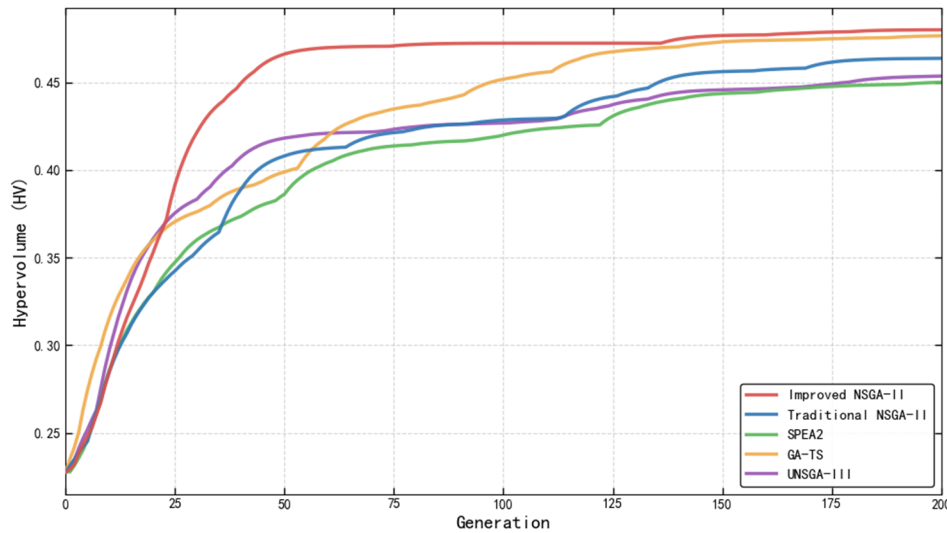


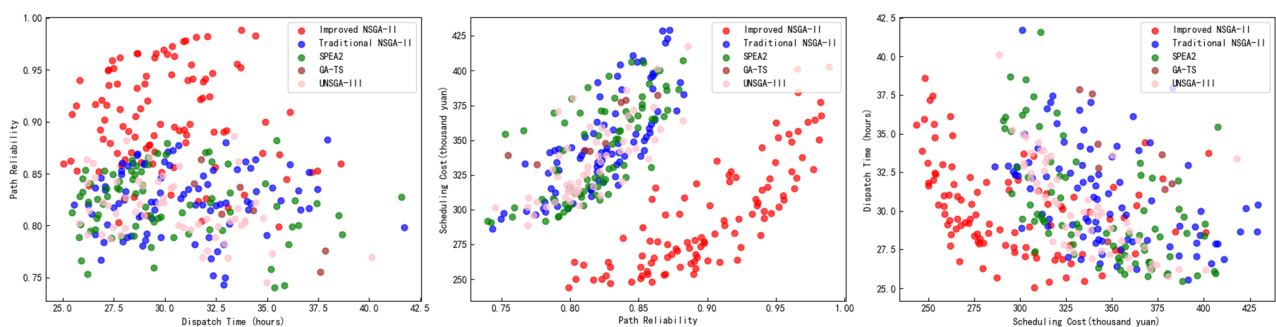
Figure 8. Comparison of HV values across generations.

As shown in Figure 8, the five algorithms exhibit differences in overall performance. The improved NSGA-II algorithm maintains the highest HV values throughout the iteration process and shows a convergence-speed advantage from the early stages, indicating that the improvement strategy guides the population effectively toward the Pareto front. GA-TS and traditional NSGA-II exhibit intermediate overall performance with relatively stable convergence trends, whereas UNSGA-III and SPEA2 have lower HV values and slower convergence rates. In summary, the improved NSGA-II algorithm outperforms the four comparison algorithms in combined convergence and diversity performance, validating the effectiveness of the proposed improvement strategy.

5.2.2. Static optimization result comparisons

(1) Comparison of Pareto front solution planes

After multiple iterations, the Pareto-front comparison for maintenance resource allocation is obtained, as shown in Figure 9.



(a) Dispatch time vs. Path reliability (b) Path reliability vs. Scheduling cost (c) Scheduling cost vs. Dispatch time

Figure 9. Comparison of Pareto front solution planes.

Figure 9 compares the scatter distributions of the Pareto fronts. As shown in Figure 9a, for the joint optimization of scheduling time and path reliability, the Pareto solution set of the improved NSGA-II algorithm is concentrated mainly in the upper-left dominant region, where scheduling time is shorter and path reliability is higher. By contrast, the solution sets of standard NSGA-II, SPEA2, GA-TS, and UNSGA-III are more dispersed. This pattern suggests that the improved NSGA-II algorithm achieves a better balance between scheduling time and path reliability. As shown in Figure 9b, for the joint optimization of path reliability and scheduling cost, the improved NSGA-II solution set outperforms those of the comparison algorithms by controlling scheduling cost while improving path reliability. As shown in Figure 9c, for the joint optimization of scheduling cost and scheduling time, the improved algorithm is concentrated in the lower-left dominant region, where scheduling time and scheduling cost are lower. Under similar scheduling time conditions, the improved algorithm also achieves lower scheduling cost than the comparison algorithms, further supporting its advantage in multi-objective coordinated optimization.

(2) Comparison of static statistical indicators

To further quantify the optimization performance of each algorithm for aviation-equipment maintenance-resource scheduling under high-disruption conditions, we compare the static statistical indicators of the Pareto-optimal solution sets. Three core metrics are evaluated: average dispatch time, average path reliability, and average scheduling cost. The results are shown in Table 14.

Table 14. Key performance indicator comparisons among algorithms.

Key Metrics	Improved NSGA-II Algorithm	SPEA2	Standard NSGA-II Algorithm	GA-TS	UNSGA-III
Average dispatch time (hours)	28.40	31.10	31.47	30.46	30.36
Average path reliability	0.93	0.82	0.84	0.83	0.83
Average scheduling cost (thousand yuan)	312.72	344.75	358.46	360.66	348.64

As shown in Table 14, the improved NSGA-II algorithm achieves the best performance across the three metrics. The average dispatch time is 28.40 h, which is lower than those of standard NSGA-II, SPEA2, GA-TS, and UNSGA-III, demonstrating stronger rapid-scheduling capability. The average path reliability reaches 0.93, exceeding those of the four comparison algorithms and indicating that the improved algorithm can enhance the route resilience of scheduling solutions. The average scheduling cost is 312.72 thousand yuan, indicating a cost advantage while maintaining better time and reliability performance. In contrast, the comparison algorithms do not achieve the same coordination among scheduling time, path reliability, and scheduling cost. These results indicate that the improved NSGA-II algorithm provides a more favorable trade-off among the three conflicting objectives and achieves superior overall optimization performance.

In summary, compared with standard NSGA-II, SPEA2, GA-TS, and UNSGA-III, the improved NSGA-II algorithm demonstrates stronger overall performance in multi-objective optimization of aviation-equipment maintenance-resource scheduling under high-disruption conditions. The algorithm shows stronger global-search capability, a greater ability to escape local optima, faster convergence, and a more uniform solution distribution. It also achieves a more favorable trade-off among scheduling

time, path reliability, and scheduling cost. These results provide efficient and reliable algorithmic support for complex multi-objective scheduling problems.

6. Conclusion

In this study, we address uncertainty and coordinated multi-objective optimization in equipment maintenance-support resource scheduling under high-disruption conditions. A multi-objective optimization model is constructed to minimize scheduling time, maximize path reliability, and minimize scheduling cost, and an improved Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is proposed to solve the model. The improved strategy combines binary-real mixed encoding, adaptive genetic operators, and a constraint-penalty mechanism. Triangular fuzzy numbers are used to quantify uncertainties in resource demand, scheduling time, and path reliability, and the centroid method is used to convert fuzzy information into computable values. Simulation results show that the fuzzy model outperforms the deterministic model in robustness and constraint satisfaction, confirming the need and practical value of fuzzy modeling. The improved NSGA-II algorithm shows advantages in convergence speed, solution-set uniformity, convergence-diversity performance, Pareto-front quality, and key scheduling indicators. In future studies, researchers should further examine dynamic features and uncertainties of equipment maintenance-support scenarios under high-disruption conditions. Existing assumptions may be relaxed by introducing dynamic task arrivals, real-time changes in resource status, coordinated maintenance task planning, regional allocation and sharing of multiple resource types, and collaborative scheduling among multiple demand points. Rescheduling strategies under dynamic disturbances should also be examined to improve responsiveness and robustness under unexpected field operating conditions. These extensions would support a more systematic maintenance-resource scheduling framework and provide more comprehensive theoretical and technical support for aviation-equipment maintenance decisions in complex high-risk operating environments.

Author contributions

Li Lan: Conceptualization, methodology, software, formal analysis, investigation, writing-original draft.

Hui Liu*, Ji-liang Tu*: Supervision, validation, project administration, writing-review and editing, funding acquisition.

Dong-hai Li, Yang Jiao, and Fu-xiang Yuan: Data curation, experimental investigation, and visualization, with contributions listed in descending order of appearance.

Use of Generative-AI tools declaration

No Artificial Intelligence (AI) tools were used in the creation of this article.

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Conflicts of interest

The authors declare that they have no conflicts of interest.

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