

Article

A Multi-Objective Cooperative Scheduling Framework for Harvesters and Grain Trucks Considering Carbon Emissions and Weather-Dependent Operational Efficiency

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Abstract

Efficient coordination between harvesters and grain trucks is essential for reducing operating cost, machinery waiting time, unnecessary travel, and carbon emissions in large-scale harvesting operations. This study develops a multi-objective cooperative scheduling framework for harvesters and grain trucks, with the objectives of minimizing total operating cost and total carbon emissions. The model integrates field operation sequencing, harvester assignment, harvester–truck service matching, machinery capacity constraints, waiting cost, and weather-dependent operational efficiency. To solve the resulting discrete and nonlinear scheduling problem, an artificial lemming algorithm with adaptive behavior selection and neighborhood cooperation (ALA-AN) is proposed. The algorithm uses a three-layer encoding structure to represent field sequences, harvester assignments, and grain truck service relationships and incorporates adaptive search, neighborhood cooperation, fast non-dominated sorting, and crowding-distance-based selection to improve Pareto-front quality. Computational experiments were conducted using real farm data and scheduling instances of different scales. The results show that the ALA-AN achieves better Pareto-front performance than the benchmark algorithms in terms of convergence, diversity, operating cost, and carbon emissions, with more evident advantages in medium- and large-scale scenarios. In the retrospective case-based comparison using Jianbian Farm records, the ALA-AN-based scheduling scheme reduced the estimated total operating cost by 5.85% and estimated total carbon emissions by 3.07% compared with the experience-based scheduling scheme. These results indicate that the proposed framework can support cost-effective and low-carbon decision making for cooperative agricultural machinery scheduling.

Keywords: agricultural machinery scheduling; harvester–grain truck coordination; multi-objective optimization; carbon emissions; sustainable agriculture

Academic Editor: Lixia Hou

Received: 17 June 2026

Revised: 11 July 2026

Accepted: 15 July 2026

Published: 16 July 2026

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1. Introduction

Large-scale grain harvesting requires close coordination between harvesters and grain trucks because field harvesting, machine transfer, grain unloading, and transportation are highly interdependent [1–3]. Therefore, cooperative scheduling has become an important approach for improving harvesting efficiency and machinery utilization in modern agricultural production. However, under limited operation windows, scheduling

decisions should not only ensure timely task completion but also consider energy consumption and environmental impacts [4,5].

With the increasing demand for low-carbon agricultural production, harvester–grain truck scheduling should be formulated as a constrained multi-objective optimization problem rather than a purely cost- or time-oriented task [6,7]. Existing studies provide useful modeling foundations, including field assignment, machinery routing, time-window constraints, capacity limitations, and harvester–truck coordination [8–10]. Nevertheless, many current models still focus mainly on operating time, transfer distance, or economic cost, while carbon emissions and weather-dependent operational efficiency are often simplified or treated as post-evaluation indicators [11–13]. These limitations motivate the development of a cooperative scheduling framework that integrates operating cost, carbon emissions, field allocation, harvester–truck service matching, and weather-dependent efficiency within a unified optimization model.

Against this background, recent studies on agricultural machinery scheduling and field operation management can be broadly grouped into three related streams: field-work organization and machinery routing, harvest logistics coordination, and low-emission intelligent field management. The first stream focuses on task allocation, route planning, cross-regional machinery services, dynamic rescheduling, and multi-machine coordination, providing useful methods for reducing travel distance, waiting time, and operating cost [14–16]. The second stream emphasizes the coordination of harvesting and transportation operations. Recent studies on collaborative harvesting and transportation planning have shown that harvester task allocation, operation sequencing, grain truck scheduling, and route planning should be optimized jointly to improve harvest logistics efficiency [17,18]. The third stream focuses on low-emission agricultural machinery systems and AI-assisted field-work management. Studies on agricultural machinery energy efficiency and CO₂ emissions indicate that reducing fuel consumption is an important pathway for low-carbon field operations, while deep-reinforcement-learning-based and intelligent decision-support methods have shown potential for improving agricultural machinery scheduling under time-window constraints and complex field conditions [15,19,20].

However, most studies still focus primarily on operational efficiency and economic objectives, while the integration of carbon emissions, field-level harvester–truck service matching, grain tank synchronization, and weather-dependent operational efficiency remains insufficient. Representative studies related to these research streams are summarized below. Cong, et al. [21] developed a machinery scheduling model that considers field area, machinery availability, field locations, and operation time windows and used a simulated annealing algorithm to obtain stable near-optimal solutions. Ma et al. [22] further considered the real-time requirements of distributed machinery services by combining soft and hard time windows in a dynamic scheduling model, where a multi-population coevolutionary genetic algorithm was used to improve response speed, machinery utilization, and scheduling robustness. Huang et al. [23] addressed multi-region agricultural machinery scheduling by integrating Voronoi-based regional division with a hybrid particle swarm optimization algorithm, reducing ineffective machinery movement and scheduling cost.

More recent studies have focused on dynamic task allocation, emergency scheduling, and intelligent decision making. Zhang, et al. [24] proposed an improved ant colony optimization method for dynamic task allocation in multi-machine collaborative operations, enabling schedule adjustment under mechanical failures or environmental changes. Pan et al. [25] developed an end-to-end deep reinforcement learning framework for emergency-oriented cooperative scheduling, jointly optimizing the time-window completion rate and total operation duration. Similarly, Wu et al. [15] formulated agricultural machin-

ery scheduling as a Markov decision process and designed a Transformer-based attention network combined with local search to improve solution quality and computational efficiency. For corn harvester–grain truck cooperative scheduling, Liu et al. [26] proposed an enhanced hybrid MOEA/D-LSA algorithm. To ensure the safety of crawler machinery, they constructed a field road network model with slope penalties, introduced a parallel safety model based on oriented bounding boxes and the separation axis theorem, and developed a three-stage steering coordination strategy. Simulation results demonstrate that the proposed approach achieves lower scheduling cost, shorter operating time, and higher coordination efficiency than conventional techniques.

Cooperative agricultural machinery scheduling has gradually shifted from single-objective optimization toward multi-objective collaborative decision making. With the development of intelligent agricultural services and large-scale mechanized production, multi-objective optimization has been increasingly applied to agricultural scheduling problems involving cost, time, service quality, machinery utilization, and operational coordination [25,27–31]. Representative studies have introduced different multi-objective models and solution algorithms. Liu et al. [32] proposed an improved multi-objective immune algorithm combining non-dominated neighbor selection and tabu search for dynamic cross-regional machinery scheduling and static zoning optimization. Li et al. [2] developed a multi-objective harvester–grain truck scheduling model to reduce non-productive waiting time and truck transfer distance and solved it using NSGA-III combined with an improved ant colony optimization algorithm. Huang et al. [23] introduced an NSGA-II-based method enhanced by simulated annealing and hybrid clustering for multi-region machinery scheduling. Guo et al. [33] proposed a multi-objective genetic algorithm with hybrid time-window priority rules and tabu search for cross-regional cooperative scheduling. More recently, Jia et al. [34] developed a bi-objective model integrating spatiotemporal clustering and service satisfaction, Miao et al. [35] proposed a Q-learning-assisted iterative greedy algorithm for multi-robot weeding scheduling, and Liu et al. [36] designed an improved marine predators algorithm for coordinating harvesters and grain transport vehicles with different capacities under time-window constraints.

These studies demonstrate that multi-objective optimization and hybrid intelligent algorithms can improve the efficiency, flexibility, and robustness of agricultural machinery scheduling. Existing methods have progressed from traditional evolutionary algorithms, such as NSGA-II and MOEAs, toward hybrid strategies that integrate simulated annealing, tabu search, ant colony optimization, Q-learning, and other adaptive mechanisms. However, significant challenges remain for large-scale field operations with complex temporal constraints and multi-machine coordination. Specifically, existing methods often suffer from slow convergence, limited solution accuracy, and restricted adaptability to environmental variability. Additionally, synchronous scheduling and spatiotemporal matching techniques have not been fully addressed by harvester–grain truck cooperative scheduling. Finally, relatively few studies explicitly integrate low-carbon objectives into harvester–grain truck cooperative scheduling under realistic farm conditions.

To address this problem, this study develops a multi objective collaborative scheduling model for harvesters and grain trucks. The model simultaneously minimizes total operating cost and total carbon emissions, and it incorporates key practical factors such as field sequencing, harvester–truck matching, machine capacity, travel and operation emissions, waiting cost, and weather-dependent operating efficiency. An artificial lemming algorithm with adaptive behavior selection and neighborhood cooperation (ALA-AN) is developed to solve the resulting nonlinear and discrete multi-objective scheduling problem. The algorithm uses a three-layer representation for fields, harvesters, and grain trucks and combines cluster-guided initialization, adaptive search selection, neighborhood cooperation, fast non-dominated sorting, and crowding-distance-based selection to

obtain high-quality Pareto solutions. The proposed framework is evaluated through computational experiments and a retrospective case-based comparison using farm records.

The main contributions of this study can be summarized as follows:

- (1) A multi-objective collaborative scheduling model is formulated for harvesters and grain trucks. The model jointly considers field operation sequencing, machine assignment, harvester–truck synchronization, capacity restrictions, waiting cost, weather-dependent operating efficiency, operating cost, and carbon emissions.
- (2) A hierarchical three-layer solution representation is designed to encode field sequences, harvester assignments, and grain truck service decisions. This representation captures the coupling structure of the scheduling problem and supports the generation of feasible collaborative schedules.
- (3) An ALA-AN multi-objective search method is proposed to solve the model. The method integrates cluster-guided initialization, adaptive search selection, and neighborhood cooperation to improve the balance between global exploration and local exploitation while maintaining Pareto-front diversity.
- (4) Computational experiments based on real farm data and instances of different scales are conducted to evaluate the proposed model and method. The results show that coordinated optimization can improve both economic and environmental performance in large-scale harvesting operations.

The remainder of this paper is structured as follows: Section 2 presents the problem description and mathematical model. Section 3 introduces the proposed solution method. Section 4 describes the experimental setup, including benchmark algorithms, parameter settings, evaluation metrics, and case data. Section 5 presents the results and discussion. Section 6 concludes the paper and outlines future research directions.

2. Materials and Methods

2.1. Problem Statement

While existing research has established multi-objective optimization frameworks and achieved notable progress in agricultural machinery cooperative scheduling, current models still exhibit certain limitations in objective formulation and constraint construction when addressing large-scale, complex operational scenarios. Specifically, most existing multi-objective optimization models primarily focus on conventional metrics such as operational duration, economic costs, and operational efficiency [37,38], often without sufficiently integrating carbon emissions during operations into the unified optimization framework. Consequently, it is difficult for these models to fully comply with the new requirements of green agriculture and carbon emission reduction strategies for farm machinery scheduling [5]. Second, most of the existing models do not fully consider the dynamic environmental factors in on-site operations, which limits the robustness and adaptability of theoretical scheduling plans when applied to actual conditions. Moreover, although previous research has addressed task allocation and route planning, the coordination constraints between harvesters and grain trucks are still not strict enough. The lack of precise spatiotemporal matching between the two types of machinery constrains the overall operational efficiency of the agricultural machinery system.

To address the above challenges, this study develops a multi-objective collaborative scheduling model for harvesters and grain trucks that explicitly incorporates carbon emissions as a core optimization objective alongside operating cost. This design is motivated by the growing demand for low-carbon and sustainable agricultural production, where inefficient machinery scheduling often leads to excessive fuel consumption, unnecessary machinery movements, and additional greenhouse gas emissions. By treating carbon emissions as a decision criterion rather than a post-evaluation indicator, the proposed

framework enables the systematic exploration of trade-offs between economic efficiency and environmental performance.

Specifically, carbon emissions are modeled from two main sources: operational emissions generated during field activities and travel emissions caused by machinery transfer and grain transportation. This dual-emission structure makes it possible to analyze how field service sequencing, route planning, and harvester–truck coordination influence the overall carbon footprint of harvesting operations. In this study, weather effects are represented by weather-dependent operational efficiency coefficients. These coefficients are used to describe the reduction or suspension of harvesting efficiency under different weather conditions. It should be noted that the present model does not treat weather as a stochastic uncertainty process; instead, weather conditions are treated as exogenous time-dependent parameters derived from historical records or operational assumptions.

Based on the notation defined in Nomenclature, weather is represented by a time-varying scenario-dependent operational-efficiency coefficient rather than by a full stochastic disturbance process. Let Ω denote the set of representative weather scenarios, including sunny, rainy, and snowy conditions. The parameter W_t^ω represents the effective harvesting-efficiency coefficient in time period t under scenario ω , and p_ω denotes the occurrence probability of scenario ω . The expected weather-adjusted coefficient is calculated as $\bar{W}_t = \sum_{\omega \in \Omega} p_\omega W_t^\omega$. Sunny conditions correspond to normal operation, rainy conditions reduce effective harvesting efficiency, and snowy conditions are treated as non-operational periods. This treatment captures the main operational impact of weather on harvesting efficiency while keeping the scheduling model solvable for large-scale cooperative machinery operations.

2.2. Model Assumptions

Before creating the multi-objective cooperative scheduling model for harvesters and grain trucks based on the ALA-AN, a set of assumptions is developed to enable the in-depth examination. These presumptions follow the rules of logic and operational viability and are based on actual agricultural production conditions.

- (1) The geographical locations, areas, and crop yields of all fields are known.
- (2) All harvesters have identical and constant operational capacities, and all grain trucks share the same vehicle type and transport performance.
- (3) Both harvesters and grain trucks depart from the same depot and return to it upon completing their tasks; grain trucks return to the depot for unloading once fully loaded.
- (4) Operational interruptions such as refueling needs or mechanical failures are not considered during the scheduling process.

These assumptions are adopted to maintain model tractability and to reflect the available operational data in the case study. In the investigated farm, the harvesters and grain trucks used during the considered harvesting period have similar technical specifications and are managed under unified operational rules; therefore, homogeneous machine parameters are used as baseline inputs. Mechanical breakdowns and operator-performance differences are not included because reliable failure records and operator-level productivity data were not available for the period studied. Terrain-dependent fuel consumption is also simplified into average travel and operation fuel consumption rates, since detailed field-level terrain resistance and soil-condition data were not recorded. These simplifications allow the model to focus on the core coupling relationship among field assignment, harvester routing, grain truck service matching, capacity constraints, and carbon emission optimization. The possible impacts of heterogeneous machinery, breakdowns, operator behavior, and terrain-dependent fuel consumption are acknowledged as important extensions for future research.

2.3. Notation and Scheduling Model

Based on the notation defined in Nomenclature, the multi-machine cooperative scheduling problem involving harvesters and grain trucks in large-scale harvesting operations is formulated as a mixed-integer programming model. The mathematical formulation is developed based on classical vehicle-routing and mixed-integer programming modeling principles.

The routing variables, depot departure/return constraints, and flow-conservation constraints follow the standard vehicle routing problem (VRP) formulation, in which binary arc variables are used to describe vehicle movements among service nodes [39]. The subtour-elimination constraints are formulated using the Miller–Tucker–Zemlin (MTZ) approach, which is widely used to prevent disconnected cycles in routing problems [40]. The field–harvester assignment, grain truck service matching, load-state, and capacity constraints are extended from pickup-and-delivery and vehicle-capacity modeling ideas to reflect the cooperative harvesting and transportation process considered in this study [41].

For the proposed cooperative scheduling problem, the optimization objectives and constraints are defined as follows:

Objective 1: Minimize the total cost, which is the sum of the total harvester cost, the total grain truck cost, and the waiting cost. The total harvester cost includes both travel cost and field-operation cost:

$$\min Z_1 = C_H + C_T + C_W \quad (1)$$

where C_H is the total harvester cost, including travel and field-operation costs; C_T is the total grain truck cost, including travel, loading, and unloading costs; and C_W is the waiting cost incurred by harvesters while waiting for grain trucks.

To maintain dimensional consistency, the fuel-related parameters are defined as fuel consumption rates rather than monetary costs. The corresponding fuel cost is obtained by multiplying fuel consumption by the diesel price P_f . The calculation formulas for C_H , C_T , and C_W are as follows:

$$C_H = P_f \left(\sum_{h \in H} \sum_{i \in F} \sum_{j \in F, j \neq i} f_{travel}^h d_{ij} x_{ij}^h + \sum_{h \in H} \sum_{i \in F \setminus \{0\}} f_{work}^h A_i x_i^h \right) \quad (2)$$

$$C_T = P_f \left(\sum_{c \in C} \sum_{i \in F} \sum_{j \in F, j \neq i} f_{travel}^c d_{ij} y_{ij}^c \right) \quad (3)$$

$$C_W = c^{penalty} \sum_{h \in H} \sum_{c \in C} \sum_{i \in F} \left(tot_i^h + t_w^h - \left(t_{ic}^h + \frac{d_{0i}}{v_c \cdot \overline{W}_t} \right) \right) \cdot x_i^h \quad (4)$$

Objective 2: The goal is to lower total carbon output, accounting for harvesters and grain trucks:

$$\min Z_2 = E_H + E_T \quad (5)$$

where E_H is the total carbon emissions of the harvesters, and E_T represents the total carbon emissions of the grain trucks.

E_H and E_T are calculated as follows:

$$E_H = \sum_{h \in H} \sum_{i, j \in F} x_{ij}^h \cdot d_{ij} \cdot CEH + \sum_{i \in F} A_i \cdot CEA \quad (6)$$

$$E_T = \sum_{c \in C} \sum_{i, j \in F} y_{ij}^c \cdot d_{ij} \cdot CEC \quad (7)$$

To ensure that all harvesters complete the total harvester area within D days, the following constraints must be met:

(1) Total harvesting area constraint

$$\sum_{h \in H} \sum_{i \in F} \bar{W}_i \times E_h \times tot_i^h \times x_i^h \geq \sum_{i \in F} A_i \quad (8)$$

(2) Single harvester operation time constraint

$$\sum_{i \in F} tot_i^h \times x_i^h \leq 12 \times D, \quad \forall h \in H \quad (9)$$

(3) Field assignment and completion constraints

To explicitly describe the relationship between field assignment and route selection, x_i^h is defined as the field-operation assignment variable, while x_{ij}^h represents the route selection variable. Equation (10) ensures that the assigned harvester completes the entire operational area of field i under the weather-dependent operating efficiency. Equation (11) guarantees that each field is assigned to exactly one harvester. Equations (12) and (13) link the assignment variable with the routing variable: if field i is assigned to harvester h , field i must be included in the operation route of harvester h with one incoming arc and one outgoing arc; otherwise, no route arc associated with field i can be selected for harvester h .

$$\sum_{h \in H} E_h \times \bar{W}_i \times t_i^h \times x_i^h = A_i, \forall i \in F \setminus \{0\} \quad (10)$$

$$\sum_{h \in H} x_i^h = 1, \forall i \in F \setminus \{0\} \quad (11)$$

$$\sum_{j \in F, j \neq i} x_{ij}^h = x_i^h, \forall i \in F \setminus \{0\}, h \in H \quad (12)$$

$$\sum_{j \in F, j \neq i} x_{ji}^h = x_i^h, \forall i \in F \setminus \{0\}, h \in H \quad (13)$$

To ensure that each harvester departs from the hangar every day and returns to the hangar after completing the task, the following constraints must be met:

$$\sum_{j \in F} x_{0j}^h = 1, \quad \forall h \in H \quad (14)$$

$$\sum_{i \in F} x_{i0}^h = 1 \quad \forall h \in H \quad (15)$$

To ensure that the number of times the harvester enters any non-warehouse site is equal to the number of times it leaves the site, the following constraints must be met:

$$\sum_{j \in F} x_{ji}^h = \sum_{j \in F} x_{ij}^h, \quad \forall h \in H, \forall i \in F \setminus \{0\} \quad (16)$$

To prevent disconnected subtours in the harvester routes, an auxiliary continuous variable u_i^h is introduced to represent the visiting order of field i in the route of harvester h . The following MTZ-type subtour-elimination constraints are added:

$$1 \leq u_i^h \leq (|F| - 1)x_i^h, \forall i \in F \setminus \{0\}, h \in H \quad (17)$$

$$u_i^h - u_j^h + (|F| - 1)x_{ij}^h \leq |F| - 2, \forall i, j \in F \setminus \{0\}, i \neq j, h \in H \quad (18)$$

Equations (17) and (18) ensure that all fields assigned to harvester h are connected to the depot through a single continuous route. Therefore, isolated cycles among fields, such as field 2–field 3–field 2, are eliminated.

To explicitly represent the service relationship among grain trucks, fields, and harvesters, a three-dimensional binary matching variable S_{ihc} is introduced. If $S_{ihc} = 1$, grain truck c provides transportation service for harvester h operating in field i ; otherwise, no such service relationship exists. The following constraints are used to link the field-harvester assignment, grain truck route selection, and service-matching relationship:

$$\sum_{c \in C} s_{ihc} = x_i^h, \forall i \in F \setminus \{0\}, h \in H \quad (19)$$

$$\sum_{j \in F, j \neq i} y_{ji}^c \geq s_{ihc}, \forall i \in F \setminus \{0\}, h \in H, c \in C \quad (20)$$

$$\sum_{j \in F, j \neq i} y_{ij}^c \geq s_{ihc}, \forall i \in F \setminus \{0\}, h \in H, c \in C \quad (21)$$

Equation (19) ensures that each assigned field-harvester operation is served by one grain truck. Equations (20) and (21) ensure route consistency for the grain truck service relationship. If grain truck c is matched with harvester h in field i , then grain truck c must enter field i through one incoming arc and leave field i through one outgoing arc; otherwise, the route of grain truck c is not required to include field i .

To explicitly incorporate the grain truck capacity into the model, a load-state variable L_{ic} is introduced, where L_{ic} denotes the grain load of truck c after providing service in field i . The load of a grain truck is accumulated according to the grain yield of the served fields and is reset to zero after the truck returns to the depot for unloading. The following load-balance and capacity constraints are added:

$$0 \leq L_{ic} \leq Q_c, \forall i \in F \setminus \{0\}, c \in C \quad (22)$$

$$L_{jc} \geq L_{ic} + \rho_j A_j \sum_{h \in H} s_{jhc} - Q_c (1 - y_{ij}^c), \forall i, j \in F \setminus \{0\}, i \neq j, c \in C \quad (23)$$

$$\sum_{i \in F \setminus \{0\}} \sum_{h \in H} \rho_i A_i s_{ihc} \leq Q_c N_c, \forall c \in C \quad (24)$$

Equation (22) restricts the load of each grain truck to its capacity. Equation (23) describes the load accumulation when truck c travels from field i to field j and serves field j . Equation (24) ensures that the total grain amount assigned to truck c does not exceed its total transportation capacity over N_c trips.

To better describe the cooperative unloading process between harvesters and grain trucks, the original static harvester capacity constraint is replaced by a dynamic grain tank loading and unloading formulation. A load-state variable B_i^h is introduced to represent the grain tank load of harvester h before operating in field i . The grain tank load increases with the harvested grain yield and is reduced when a matched grain truck provides unloading service. The following constraints describe grain accumulation, full-tank triggering, unloading service, and capacity recovery:

$$0 \leq B_i^h \leq V_h^{\max}, \forall i \in F \setminus \{0\}, h \in H \quad (25)$$

$$B_i^h + \rho_i A_i x_i^h \leq V_h^{\max} + V_h^{\max} \sum_{c \in C} s_{ihc}, \forall i \in F \setminus \{0\}, h \in H \quad (26)$$

$$B_i^h + \rho_i A_i x_i^h - V_h^{\max} \leq M \sum_{c \in C} s_{ihc}, \forall i \in F \setminus \{0\}, h \in H \quad (27)$$

Equation (25) ensures that the grain tank load of each harvester never exceeds its maximum capacity. Equation (26) describes grain accumulation during field operations and allows capacity recovery when a matched grain truck provides unloading service. Equation (27) requires grain truck unloading service to be activated when the accumulated grain load reaches the capacity limit. Therefore, the revised formulation no longer assumes that a harvester carries all harvested grain across multiple fields without unloading, where M is a sufficiently large positive constant.

The following requirements must be met for every grain truck to fulfill its designated transportation tasks:

$$\sum_{j \in F} y_{0j}^c + \sum_{j \in F} y_{j0}^c = 2N_c, \forall c \in C \quad (28)$$

The guidelines that follow must be achieved to guarantee that every grain truck leaves and returns to the machine depot an equal number of times, to prevent trucks from departing without returning, and to guarantee that transportation routes are closed loops:

$$\sum_{j \in F} y_{0j}^c = \sum_{j \in F} y_{j0}^c, \forall c \in C \quad (29)$$

To ensure that grain trucks can adequately meet the demands of harvesters, the time from when a harvester's grain tank is empty until it becomes full, plus the unloading time and the maximum allowable waiting time, should be no less than the time required for a grain truck to return to the depot for unloading after being fully loaded and then travel back to field i . Furthermore, the impact of external factors such as weather on operational efficiency must be considered. In this context, two distinct scenarios are analyzed: one where the harvester does not need to relocate to another field, and another where the harvester has not reached full capacity but the harvesting operations in field i have been completed.

To determine whether a harvester needs to move from field i to field j , it is necessary to calculate the area of the remaining unharvested field required for the harvester's grain tank to reach full capacity, denoted as $A_h^{\max}$. The calculation formula for $A_h^{\max}$ is shown as Equation (30):

$$A_h^{\max} = \frac{V_h^{\max} \times \gamma}{\rho_i} \quad (30)$$

When $A_{ih}^R \geq A_h^{\max}$, the time constraints that must be satisfied for the cooperative operation between the harvesters and the grain trucks are as follows:

$$\left[t_i^h + \frac{\gamma \times V_h^{\max}}{\rho_i \times E_h \times \bar{W}_t} + t_w^h - \min_c \left(t_{ic}^h + \frac{d_{i0} + d_{0i}}{v_c \times \bar{W}_t} + t_c^{\text{unload}} \right) \right] x_i^h \geq 0, h \in H \quad (31)$$

When $A_{ih}^R < A_h^{\max}$, the time constraint conditions that must be met for the coordinated operation of grain trucks and harvesters are:

$$\left[\left(t_i^h + \frac{A_{ih}^R}{E_h \times \bar{W}_t} \right) x_i^h + \left(\frac{d_{ij}}{v_h} + \frac{A_h^{\max} - A_{ih}^R}{E_h \times \bar{W}_t} + t_w^h \right) x_j^h - \min_c \left[\left(t_{ic}^h + \frac{d_{i0}}{v_c \times \bar{W}_t} + t_c^{\text{unload}} \right) x_i^h + \frac{d_{0j}}{v_c \times \bar{W}_t} x_j^h \right] \right] \geq 0 \quad (32)$$

In summary, the multi-machine cooperative scheduling problem of harvesters and grain trucks can be formulated as a mathematical model with the objectives of minimizing total scheduling cost and total carbon emissions as follows:

$$\begin{aligned}
\min Z_1 &= P_f \left(\sum_{h \in H} \sum_{i \in F} \sum_{j \in F, j \neq i} f_{travel}^h d_{ij} x_{ij}^h + \sum_{h \in H} \sum_{i \in F \setminus \{0\}} f_{work}^h A_i x_i^h \right) + P_f \left(\sum_{c \in C} \sum_{i \in F} \sum_{j \in F, j \neq i} f_{travel}^c d_{ij} y_{ij}^c \right) + c^{penalty} \sum_{h \in H} \sum_{c \in C} \sum_{i \in F} \left(tot_i^h + t_w^h - \left(t_{ic}^h + \frac{d_{0i}}{v_c \times \bar{W}_t} \right) \right) \cdot x_i^h \\
\min Z_2 &= \sum_{h \in H} \sum_{i, j \in F} x_{ij}^h \cdot CEH + \sum_{i \in F} A_i \cdot CEA + \sum_{c \in C} \sum_{i, j \in F} y_{ij}^c \cdot d_{ij} \cdot CEC \\
s.t. & \begin{cases} \sum_{h \in H} \sum_{i \in F} \bar{W}_i \times E_h \times tot_i^h \times x_i^h \geq \sum_{i \in F} A_i \\ \sum_{i \in F} tot_i^h \times x_i^h \leq 12 \times D, \forall h \in H \\ \sum_{h \in H} E_h \times \bar{W}_i \times t_i^h \times x_i^h = A_i, \forall i \in F \setminus \{0\} \\ \sum_{h \in H} x_i^h = 1, \forall i \in F \setminus \{0\} \\ \sum_{j \in F, j \neq i} x_{ij}^h = x_i^h, \forall i \in F \setminus \{0\}, h \in H \\ \sum_{j \in F, j \neq i} x_{ji}^h = x_i^h, \forall i \in F \setminus \{0\}, h \in H \\ \sum_{j \in F} x_{0j}^h = 1, \forall h \in H \\ \sum_{i \in F} x_{i0}^h = 1, \forall h \in H \\ \sum_{j \in F} x_{ji}^h = \sum_{j \in F} x_{ij}^h, \forall h \in H, \forall i \in F \setminus \{0\} \\ 1 \leq u_i^h \leq (|F| - 1) x_i^h, \forall i \in F \setminus \{0\}, h \in H \\ u_i^h - u_j^h + (|F| - 1) x_{ij}^h \leq |F| - 2, \forall i, j \in F \setminus \{0\}, i \neq j, h \in H \\ \sum_{c \in C} s_{ihc} = x_i^h, \forall i \in F \setminus \{0\}, h \in H \\ \sum_{j \in F, j \neq i} y_{ji}^c \geq s_{ihc}, \forall i \in F \setminus \{0\}, h \in H, c \in C \\ \sum_{j \in F, j \neq i} y_{ij}^c \geq s_{ihc}, \forall i \in F \setminus \{0\}, h \in H, c \in C \\ 0 \leq L_{ic} \leq Q_c, \forall i \in F \setminus \{0\}, c \in C \\ L_{jc} \geq L_{ic} + \rho_j A_j \sum_{h \in H} s_{jhc} - Q_c (1 - y_{ij}^c), \forall i, j \in F \setminus \{0\}, i \neq j, c \in C \\ \sum_{i \in F \setminus \{0\}} \sum_{h \in H} \rho_i A_i s_{ihc} \leq Q_c N_c, \forall c \in C \\ 0 \leq B_i^h \leq V_h^{max}, \forall i \in F \setminus \{0\}, h \in H \\ B_i^h + \rho_i A_i x_i^h \leq V_h^{max} + V_h^{max} \sum_{c \in C} s_{ihc}, \forall i \in F \setminus \{0\}, h \in H \\ B_i^h + \rho_i A_i x_i^h - V_h^{max} \leq M \sum_{c \in C} s_{ihc}, \forall i \in F \setminus \{0\}, h \in H \\ \sum_{j \in F} y_{0j}^c + \sum_{j \in F} y_{j0}^c = 2N_c, \forall c \in C \\ \sum_{j \in F} y_{0j}^c = \sum_{j \in F} y_{j0}^c, \forall c \in C \\ \left[t_i^h + \frac{\gamma \times V_h^{max}}{\rho_i \times E_h \times \bar{W}_t} + t_w^h - \min_c \left(t_{ic}^h + \frac{d_{i0} + d_{0i}}{v_c \times \bar{W}_t} + t_c^{unload} \right) \right] x_i^h \geq 0, h \in H \\ \left[\left(t_i^h + \frac{A_{ih}^R}{E_h \times \bar{W}_t} \right) x_i^h + \left(\frac{d_{ij}}{v_h} + \frac{A_h^{max} - A_{ih}^R}{E_h \times \bar{W}_t} + t_w \right) x_j^h - \min_c \left[\left(t_{ic}^h + \frac{d_{i0}}{v_c \times \bar{W}_t} + t_c^{unload} \right) x_i^h + \frac{d_{0j}}{v_c \times \bar{W}_t} x_j^h \right] \right] \geq 0 \\ x_{ij}^h, y_{ij}^c, x_i^h \in \{0, 1\}, tot_i^h \geq 0, i, j = 0, 1, 2, \dots, n; h = 1, 2, \dots, m \end{cases} \quad (33)
\end{aligned}$$

3. The Proposed Method

The cooperative scheduling model formulated in Section 2 involves both continuous and discrete decision variables, along with nonlinear relationships arising from operation durations, route selection, capacity limitations, and waiting penalties. These features render the problem highly coupled and computationally challenging. The standard ALA [42], which is primarily designed for continuous optimization, is therefore insufficient for handling such a combinatorial and constraint-intensive scheduling task. To improve the solution quality and computational efficiency of the proposed cooperative scheduling model, this study develops an ALA-AN by introducing targeted enhancements to the ALA, enabling it to effectively address the multi-objective and strongly constrained characteristics of agricultural machinery cooperative scheduling. Figure 1 illustrates the process framework of the proposed model, which includes the constraints considered in the

cooperative scheduling model, the solution method ALA-AN, and the objectives of the model.

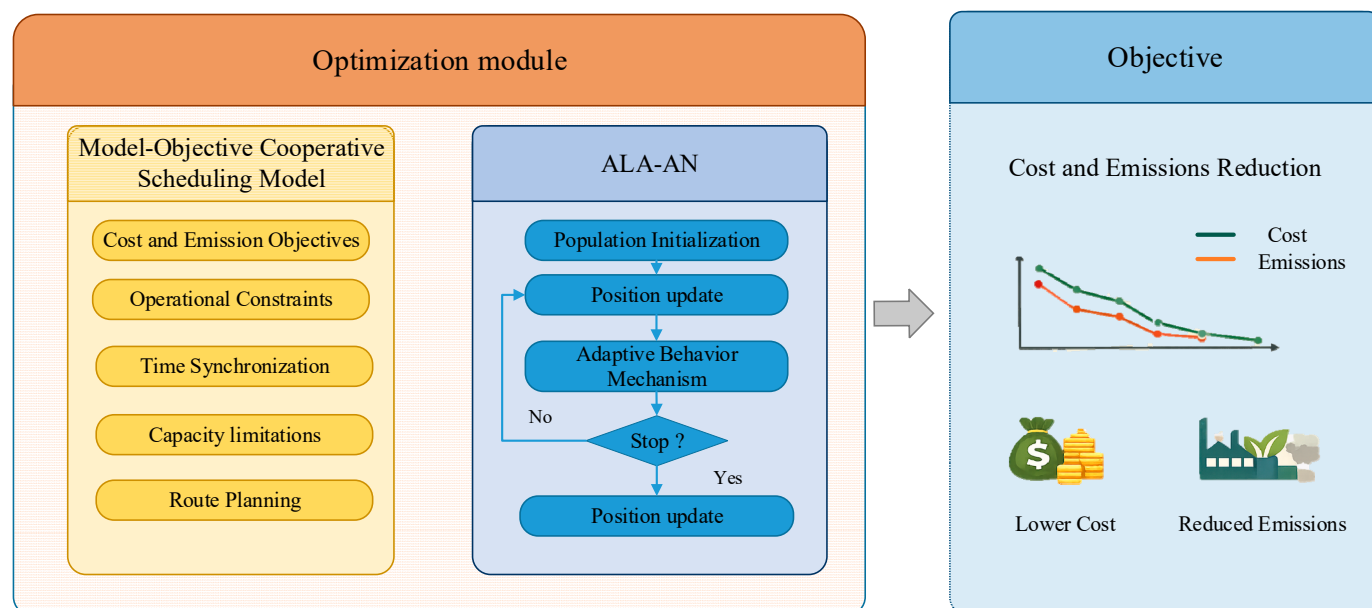


Figure 1. Framework of the proposed cooperative scheduling model.

3.1. Three-Layer Cooperative Encoding Structure

The algorithm is designed with a three-layer cooperative encoding structure so that individuals can accurately represent the actual numbers of fields, harvesters, and grain trucks in operational scenarios. This structure ensures the feasibility of the solution by randomly generating the agricultural machinery scheduling plan into three inter-related real vectors, corresponding to the coordinated matching relationship between field allocation, harvester, and grain truck, thereby achieving accurate expression and efficient optimization of complex scheduling information. Specifically, the first layer of the encoding represents the fields, the second layer represents the harvesters, and the third layer represents the grain trucks. To illustrate the three-layer cooperative encoding and decoding process, a scheduling example involving 9 fields, 3 harvesters, and 3 grain trucks is presented in Table 1. The table shows the original real-valued encoding, sorted indices, decoded field sequence, harvester assignment, truck assignment, and the final field–harvester–truck mapping.

Table 1. Example of the three-layer cooperative encoding and decoding process.

Step	Layer	Gene 1	Gene 2	Gene 3	Gene 4	Gene 5	Gene 6	Gene 7	Gene 8	Gene 9	Unit/Type
Original encoding	Field layer	0.51	0.12	0.01	0.39	0.12	0.54	0.32	0.28	0.11	Dimensionless real value
Decoded result	Field number	8	3	1	7	4	9	6	5	2	Field index
Original encoding	Harvester layer	0.23	0.61	0.32	0.22	0.4	0.13	0.44	0.2	0.15	Dimensionless real value
Sorted index	Harvester index number	5	9	6	4	7	1	8	3	2	Index
Decoded result	Harvester number	2	3	2	2	3	1	3	1	1	Harvester index
Original encoding	Truck layer	0.33	0.21	0.17	0.08	0.34	0.16	0.34	0.23	0.28	Dimensionless real value

Sorted index	Truck index number	7	4	3	1	8	2	9	5	6	Index
Decoded result	Truck number	3	2	1	1	3	1	3	2	2	Truck index

As shown in Table 1, the original encoding rows are dimensionless real-valued vectors generated by the algorithm. The decoded rows represent field indices, harvester indices, truck indices, and sorted ranks rather than physical quantities. The field layer is used to determine the operation sequence of fields. The harvester layer determines which harvester is assigned to each decoded field, while the truck layer determines which grain truck provides transport service for the corresponding harvester–field pair. Therefore, the three-layer encoding structure can simultaneously represent field sequencing, harvester assignment, and grain truck service matching in a unified individual representation.

3.2. Real Valued Encoding-Decoding Method Based on Ascending Index Mapping

Since the ALA employs real-valued encoding, the continuous solutions generated during iterative updates must be transformed into discrete scheduling decisions. To address this issue, a real-valued encoding–decoding method based on ascending index mapping is designed. This method converts continuous vectors into field sequences, harvester assignments, and truck assignments without using rounding, ceiling, or flooring operations, thereby avoiding duplicate field numbers and infeasible decoded solutions.

For the field layer, the real-valued vector is sorted in ascending order. The rank of each gene in the sorted sequence is then used to determine the corresponding field number. In this way, the field layer is decoded into a complete permutation of field indices. If two or more genes have identical values, their original gene positions are used to break the tie, so that each field number appears only once. Taking the field layer in Table 1 as an example, the original real-valued vector is decoded into the field sequence (8,3,1,7,4,9,6,5,2).

For the harvester and truck layers, the same ascending-rank mapping rule is first applied to obtain the sorted ranks of all genes. The sorted ranks are then divided into groups according to the number of available harvesters or grain trucks. In the example shown in Table 1, there are 9 fields, 3 harvesters, and 3 grain trucks. Therefore, every three sorted ranks are assigned to one machine. Specifically, ranks 1–3 are assigned to machine 1, ranks 4–6 are assigned to machine 2, and ranks 7–9 are assigned to machine 3. According to this rule, the harvester layer is decoded as (2,3,2,2,3,1,3,1,1), and the truck layer is decoded as (3,2,1,1,3,1,3,2,2).

After decoding the three layers, a one-to-one mapping relationship among field number, harvester number, and truck number is established for each gene position. For example, in the first gene position of Table 1, the decoded field number is 8, the corresponding harvester number is 2, and the corresponding truck number is 3. This means that field 8 is assigned to harvester H_2 , and grain truck C_3 provides transport service for harvester H_2 at this field. The remaining gene positions can be interpreted in the same way.

According to the decoded mapping in Table 1, the scheduling scheme can be summarized as follows. Harvester H_1 is assigned to fields 9, 5, and 2, and its route is $0 \rightarrow 9 \rightarrow 5 \rightarrow 2 \rightarrow 0$, where 0 represents the machinery depot. Harvester H_2 is assigned to fields 8, 1, and 7, and its route is $0 \rightarrow 8 \rightarrow 1 \rightarrow 7 \rightarrow 0$. Harvester H_3 is assigned to fields 3, 4, and 6, and its route is $0 \rightarrow 3 \rightarrow 4 \rightarrow 6 \rightarrow 0$. Correspondingly, grain truck C_1 serves fields 1, 7, and 9, and its route is $0 \rightarrow 1 \rightarrow 7 \rightarrow 9 \rightarrow 0$; grain truck C_2 serves fields 3, 5, and 2, and its route is $0 \rightarrow 3 \rightarrow 5 \rightarrow 2 \rightarrow 0$; and grain truck C_3 serves fields 8, 4, and 6, and its route is $0 \rightarrow 8 \rightarrow 4 \rightarrow 6 \rightarrow 0$.

The decoded scheduling scheme provides the basis for subsequent route construction and feasibility evaluation. Specifically, the field sequence determines the visiting order,

the harvester assignment determines the operation responsibility of each harvester, and the truck assignment determines the service relationship between grain trucks and harvester–field pairs. After decoding, the generated solution is further checked according to route continuity, machinery capacity, time-window, grain tank synchronization, and other operational constraints before fitness evaluation.

3.3. Population Initialization Combining K-Means Clustering with Random Perturbation Strategy

To improve population diversity and the quality of initial solutions, a population initialization method combining K-means clustering and a random perturbation strategy is designed for the proposed three-layer cooperative encoding structure. In this method, each individual consists of three layers, representing the field sequence, harvester assignment, and grain truck assignment, respectively. The initialization process should maintain the logical consistency among these three layers so that the generated individuals can reflect feasible field–harvester–truck matching relationships.

Based on the real-valued encoding–decoding method described in Section 3.2, the initial population can be generated directly in the decoded three-layer form, including field numbers, harvester numbers, and truck numbers, as illustrated in Table 1. This design avoids repeated transformation between the original real-valued vectors and the decoded integer representation during initialization, thereby improving the generation efficiency of the initial population. When the population size is Np , the specific initialization procedure is described as follows:

Step 1: Initialize the field number layer.

Randomly generate an integer vector of length n , where each element is an integer within the interval $[1, n]$.

Step 2: Initialize the harvester number layer.

First, based on the total number of fields n and the number of harvesters m , compute the number of fields each harvester needs to process. Let the quotient of n/m be k and the remainder be r . If the remainder is r , then assign $k + 1$ fields to each of the first r harvesters, and assign k fields to each of the remaining $m - r$ harvesters.

Next, specific fields are assigned to the harvesters. To enhance the diversity of the initial population, $0.5Np$ individuals are randomly generated using the following procedure: For each harvester i ($i = 1, 2, \dots, m$), if it is assigned to process p fields, then repeat the value i exactly p times to form an integer vector Z . Then, randomly generate a vector q of n non-repeated integers within the interval $[1, n]$. Use q as an index to reorder vector Z , thereby generating one individual for the harvester number layer. Repeat the above process $0.5Np$ times to obtain $0.5Np$ individuals.

Finally, $0.5Np$ individuals are generated by using the K-means clustering and random perturbation strategy. Considering the spatial distribution characteristics of fields and the influence of harvester transfer distance on operational costs, the K-means clustering algorithm is adopted to spatially cluster the fields and the fields are divided into m categories, with each category corresponding to the operation plot of one harvester. The specific steps are as follows:

The coordinates of the i -th field are (x_i, y_i) , and the goal of clustering is to divide the plot into m categories, each corresponding to a harvester's operating plot. Among them, the centroid C_j of each category is defined as the arithmetic mean of the coordinates of all plots within the category, and the calculation formula for C_j is:

$$C_j = (\bar{x}_j, \bar{y}_j) = \left(\frac{1}{p_j} \sum_{i=1}^{p_j} x_i, \frac{1}{p_j} \sum_{i=1}^{p_j} y_i \right) \quad (34)$$

where C_j is the centroid coordinates of the j -th cluster, p_j denotes the number of fields included in the C_j , and (x_i, y_i) indicates the coordinates of the i -th field in the cluster.

K -means clustering iteratively divides the field categories and updates the centroids of each category through the minimum distance criterion until the division results of each category remain unchanged. Ultimately, m classes with good spatial continuity are obtained, enabling adjacent fields geographically to be allocated to the same harvester as much as possible, thereby reducing the operation cost and energy consumption of the harvester.

Using the K -means clustering result, one individual $Z_{0.5Np+1}$ in the population can be generated. The remaining $0.5Np - 1$ individuals are produced via random perturbation. The procedure is as follows: randomly generate two unequal integers a and b within the $[1, n]$, and then reverse the order of the genes from position a to b in $X_{0.5Np+1}$ to create a new individual. Repeat this process until $0.5Np - 1$ individuals have been generated.

To summarize, the population initialization method integrating K -means clustering with random perturbation effectively balances population diversity and the quality of the initial solutions.

Step 3: Initialize the truck number layer.

The truck number layer, which allocates grain trucks to harvesters, is generated using the same method as the harvester number layer.

By integrating K -means clustering with random perturbation, $0.5Np$ individuals are randomly generated to ensure good diversity in the initial population. The combination of K -means clustering and random perturbation for these $0.5Np$ individuals allows the generated initial population to balance both diversity and solution quality.

3.4. Exploration Stage

The exploration stage includes long-distance migration and burrowing. During the long-distance migration, lemmings randomly select individuals according to their current location and population and jointly explore the search space, so as to find a habitat with more abundant food resources and obtain better living conditions and resources. This behavior primarily enhances global exploration capability and prevents the algorithm from getting trapped in local optima. To simulate this behavior, the position update formula for the long-distance migration phase is given by Equation (35):

$$Z_i(t+1) = Z_{best}(t) + F \times \overline{BM} \times (\overline{R} \times (Z_{best}(t) - Z_i(t)) + (1 - \overline{R}) \times (Z_i(t) - Z_a(t))) \quad (35)$$

where $Z_i(t+1)$ is the position of the i -th individual at iteration $t+1$, $Z_{best}(t)$ represents a global guiding solution selected from the external Pareto archive at iteration t using a crowding-distance-based selection strategy, $Z_i(t)$ denotes the position of the i -th lemming at iteration t , $Z_a(t)$ is a randomly selected lemming from the population, and a is an integer index ranging from 1 to Np .

$\overline{BM}$ is a random vector generated by Brownian motion, which uses dynamic and uniform step sizes to explore potential regions within the search space. The step size of standard Brownian motion is obtained from the probability density function of a normal distribution with a mean of 0 and a variance of 1, as shown below.

$$f_{BM}(x; 0, 1) = \frac{1}{\sqrt{2\pi}} \times \exp\left(-\frac{x^2}{2}\right) \quad (36)$$

F serves as a marker for changing the search direction and is calculated by Equation (37):

$$F = \begin{cases} 1, & \text{if } \lfloor 2 \times rand + 1 \rfloor = 1 \\ -1, & \text{if } \lfloor 2 \times rand + 1 \rfloor = 2 \end{cases} \quad (37)$$

where $\lfloor \cdot \rfloor$ denotes the floor function.

$$\bar{R} = 2 \times \text{rand}(1, \text{Dim}) - 1 \quad (38)$$

Here, *rand* is a random number uniformly distributed within $[-1, 1]$.

Lemmings dig holes in their habitats to build a complex underground tunnel system and provide them with safe shelter and food storage space. In this process, they dig new caves according to the location of existing caves and randomly select individuals from the population, so as to further explore and optimize the local environment. The corresponding position update formula is given in Equation (39):

$$Z_i(t+1) = Z_i(t) + F \times L \times (Z_{\text{best}}(t) - Z_b(t)) \quad (39)$$

where $Z_b(t)$ is an individual randomly selected from the population, and L is a random number related to the current iteration count. The calculation formula for L is as follows:

$$L = \text{rand} \times \left(1 + \sin\left(\frac{t}{2}\right) \right) \quad (40)$$

where t is the current iteration count.

3.5. Position Update for Predator Evasion Based on Neighborhood Cooperation

Lemmings move around their burrows at will, establishing a relatively limited feeding area within the habitat, the size of which depends on the abundance and availability of food resources. To maximize food access, lemmings wander randomly within this area. The position update formula for this stage is as follows:

$$Z_i(t+1) = Z_{\text{best}}(t) + F \times \text{spiral} \times \text{rand} \times Z_i(t) \quad (41)$$

$$\text{spiral} = \text{radius} \times (\sin(2\pi \times \text{rand}) + \cos(2\pi \times \text{rand})) \quad (42)$$

$$\text{radius} = \sqrt{\sum_{j=1}^{\text{Dim}} (z_{\text{best},j}(t) - z_{i,j}(t))^2} \quad (43)$$

where $z_{i,j}(t)$ denotes the j -th dimension of the i -th individual in the population at iteration t , and $z_{\text{best},j}(t)$ represents the j -th dimension of the best individual in the population at iteration t .

The predator evasion stage based on neighborhood cooperation incorporates local neighborhood information while retaining global guidance and random perturbations, enabling cooperative fine-grained search and maintaining population diversity. By introducing a neighborhood cooperation term, the update mechanism encourages individuals to perform more structured searches within a local region. This not only reduces excessive reliance on the global best solution but also preserves moderate random jumps to strengthen global exploration, thereby markedly improving the algorithm's robustness and convergence accuracy in complex search spaces. The predator evasion position update formula based on the neighborhood cooperation mechanism is outlined below:

$$Z_i(t+1) = 0.3 \times (Z_{\text{best}}(t) + Z_i(t)) + A_1 \times (Z_{\text{best}}(t) - Z_i(t)) + A_2 \times (Z_k^*(t) - Z_i(t)) \quad (44)$$

where $Z_i(t)$ denotes the i -th individual in the t -th iteration, $Z_k^*(t)$ represents a local guiding solution selected from the non-dominated solutions within the k -nearest neighborhood of individual i , using the crowding-distance-based selection strategy, and $A_2 \times (Z_k^*(t) - Z_i(t))$ constitutes the neighborhood cooperation term. The neighborhood size is set to 20% of the population size, i.e., $k = 0.2Np$.

The parameters A_1 and A_2 are calculated using the following formulas:

$$A_1 = (2 \times \text{rand} - 1) \times (1 - t / T_{\text{max}}) \quad (45)$$

$$A_2 = e^{bl} \times \cos(2\pi l) \quad (46)$$

where rand and l are uniformly distributed random numbers in the $[0,1]$, and $b = 1$.

To visually compare the distribution of offspring in the solution space and the quality of offspring generated by Equation (44), a two-dimensional example is considered. Let the positions of Z_{best} , Z_k^* , and Z_i be $(0,0)$, $(4,4)$, and $(2,5)$, respectively. For Equation (44), 1000 random combinations of A_1 and A_2 values are generated, and the corresponding distribution of offspring individuals is displayed in Figure 2.

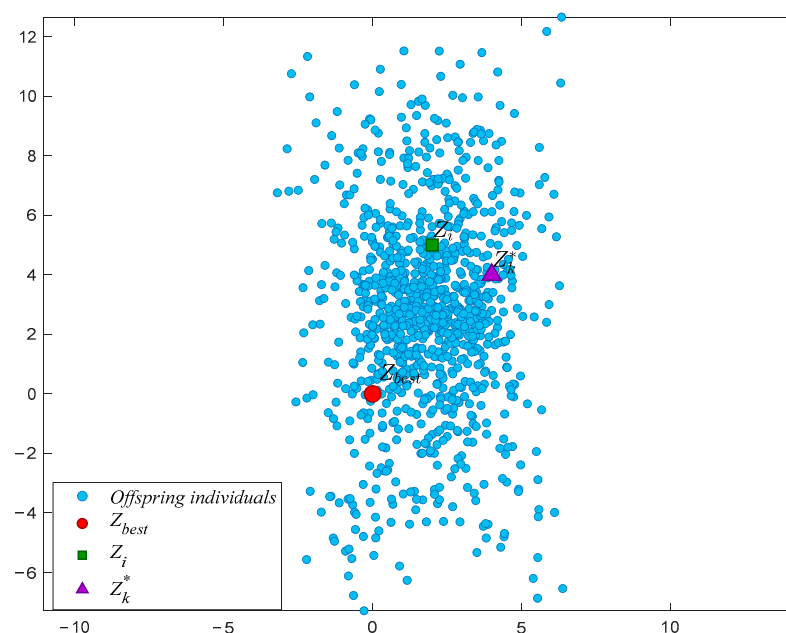


Figure 2. Distribution of offspring in the solution space generated by Equation (44).

As observed in Figure 2, the offspring generated by Equation (44) cover a broader range in the solution space, indicating enhanced exploration capability of the algorithm. Meanwhile, many individuals are gathered near Z_{best} and Z_k^* , which increases the number of potential solutions generated. This indicates that Equation (44) considers the distribution characteristics and quality of offspring in the solution space when generating new solutions, achieving coordination between exploration and exploitation. After introducing the neighborhood cooperation term in Equation (44), the distribution of offspring around Z_{best} and Z_k^* is more uniform, while a certain number of offspring individuals are still retained in other regions, which effectively balances the global exploration and local exploitation capabilities of the algorithm.

In summary, the position update formula for predator evasion integrated with the neighborhood cooperation mechanism can significantly improve algorithm performance. On the one hand, the distribution range of offspring in the solution space is wider, enhancing the global exploration ability. On the other hand, there are sufficient and evenly distributed high-quality individuals near Z_{best} and Z_k^* , effectively improving local exploitation efficiency and overall solution quality. Therefore, this improvement strategy achieves collaborative optimization of global search and local exploitation, significantly enhancing the overall performance of the algorithm.

3.6. Leader Selection Mechanism in the Multi-Objective ALA-AN

Since the proposed scheduling problem is a multi-objective optimization problem, there is no unique global optimum that can be directly used as the guiding solution in the position-update equations. Therefore, in the proposed ALA-AN, Z_{best} does not denote a single-objective global optimum. Instead, it represents a global guiding solution selected from an external Pareto archive.

At each iteration, the current population $P(t)$ and the external archive $A(t-1)$ are combined:

$$R(t) = P(t) \cup A(t-1) \quad (47)$$

where $R(t)$ denotes the combined population. Fast non-dominated sorting is then performed on $R(t)$, and the first non-dominated front is used to update the external Pareto archive $A(t)$, following the Pareto-based selection framework widely used in multi-objective evolutionary algorithms [43,44].

If the number of non-dominated solutions exceeds the maximum archive size N_A , a crowding-distance-based truncation strategy is applied to retain well-distributed Pareto solutions.

The crowding distance is used to measure the density of solutions around each non-dominated solution in the objective space. For the r -th non-dominated solution Z_r , the crowding distance $CD(Z_r)$ is calculated as:

$$CD(Z_r) = \sum_{m=1}^M \frac{f_m(Z_{r+1}^m) - f_m(Z_{r-1}^m)}{f_m^{\max} - f_m^{\min}} \quad (48)$$

where M is the number of objectives. In this study, $M = 2$, corresponding to total operating cost and total carbon emissions. $f_m(Z_r)$ represents the value of the m -th objective function for solution Z_r . $f_m^{\max}$ and $f_m^{\min}$ are the maximum and minimum values of the m -th objective in the current Pareto archive, respectively. Z_{r+1}^m and Z_{r-1}^m denote the two neighboring solutions of Z_r after sorting the archive according to the m -th objective. Boundary solutions are assigned a sufficiently large crowding distance to preserve the extreme solutions of the Pareto front.

Based on the crowding distance, the global guiding solution $Z_{best}(t)$ is selected from the external Pareto archive as:

$$Z_{best}(t) = \arg \max_{Z_r \in A(t)} CD(Z_r) \quad (49)$$

Similarly, the local guiding solution $Z_k^*(t)$ used in the neighborhood cooperation mechanism is also selected according to a Pareto-based rule. For each individual $Z_i(t)$, its k -nearest neighborhood $N_i^k(t)$ is first constructed, where k is set as 20% of the population size. Non-dominated sorting is then performed within this neighborhood to obtain the neighborhood non-dominated solution set $ND_i^k(t)$. The local guiding solution is selected as:

$$Z_k^*(t) = \arg \max_{Z_r \in ND_i^k(t)} CD(Z_r) \quad (50)$$

where $N_i^k(t)$ denotes the set of non-dominated solutions in the k -nearest neighborhood of individual $Z_i(t)$. Therefore, $Z_k^*(t)$ represents a local Pareto guiding solution selected from the neighborhood non-dominated solution set rather than a single-objective local optimum.

Through this mechanism, $Z_{best}(t)$ provides global Pareto guidance from the external archive, while $Z_k^*(t)$ provides local Pareto guidance from the neighborhood of each individual. The use of crowding distance helps maintain the diversity of the Pareto front and prevents the search from being excessively concentrated in a small region of the objective space. Consequently, the proposed leader-selection mechanism improves the balance between convergence and diversity in the multi-objective ALA-AN.

3.7. Adaptive Behavior Selection Mechanism

By analyzing the exploration and exploitation characteristics of the four stages of long-distance migration, digging, foraging, and predator evasion in the ALA, it can be concluded that the long-distance migration and digging stages mainly undertake global search tasks, and their exploration ability is significantly stronger than that of the foraging and predator evasion stages. Relatively speaking, the foraging and evasion stages have stronger local development capabilities, with the foraging stage having the most prominent exploitation ability, which is superior to the evasion stage.

From the ALA, it can be known that during the exploration phase, long-distance migration is executed when $E > 1$ and $\text{rand} < 0.3$; otherwise, digging holes is performed. During the exploitation phase, perform foraging when $E \leq 1$ and $\text{rand} < 0.5$; otherwise, conduct predator evasion, where $E(t) = 4 \times \arctan(1 - t/T_{\max}) \times \ln(1/\text{rand})$. Due to the fixed constants 0.3 and 0.5, the selection probabilities of the four behaviors remain unchanged, without considering the dynamic changes in search requirements during the iteration process. Therefore, it is difficult to adaptively balance exploration and exploitation capabilities during the iteration process.

An adaptive behavior selection mechanism is proposed in response to the above problems. By introducing a selection probability P that dynamically adjusts with the number of iterations, the algorithm can adaptively balance exploration and exploitation capabilities based on changes in demand during the search process, thereby improving overall optimization performance. The selection probability P is calculated as follows:

$$P = \text{rand} \times e^{-\frac{t}{T_{\max}}} \quad (51)$$

where t is the iteration number, $T_{\max}$ is the maximum number of iterations, and rand is a random number between $[0,1]$.

To intuitively observe the trend of the selection probability P as the number of iterations increases, the trend of the selection probability P as the number of iterations increases when $T_{\max} = 1000$, as illustrated in Figure 3.

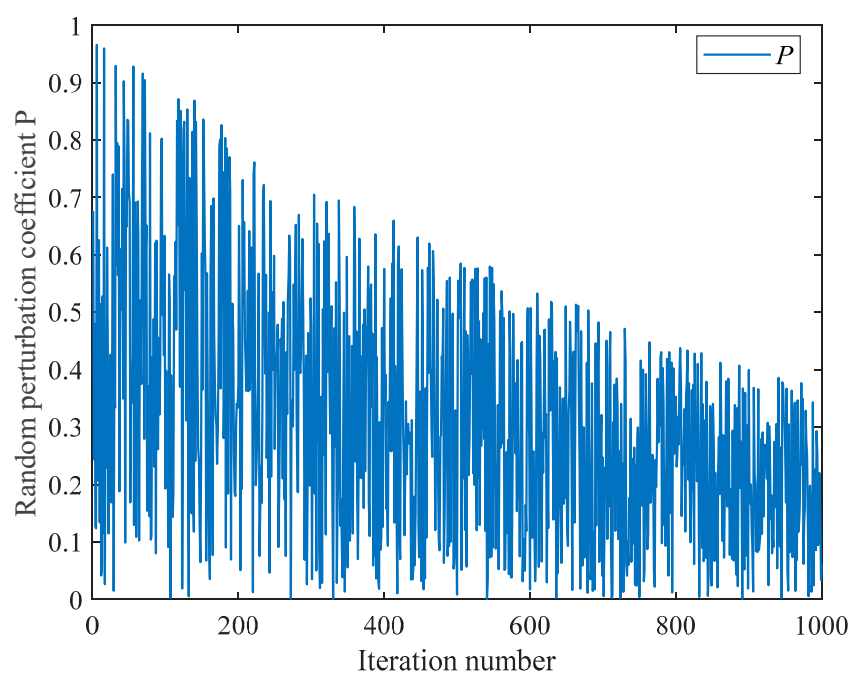


Figure 3. Variation trend of the selection probability P with increasing iterations.

According to Figure 3, the selection probability P exhibits an oscillatory decreasing trend as iterations advance, shifting from generally larger values in early stages to mostly lower values in later phases. According to the adaptive dynamic behavior selection strategy, this pattern indicates the algorithm's stronger inclination toward long-distance migration and predator evasion during initial iterations while progressively favoring digging and foraging behaviors in later stages. From the perspective of dynamically changing search requirements, the proposed adaptive dynamic behavior selection mechanism is capable of automatically adjusting the balance between exploration and exploitation at different evolutionary stages. Consequently, it achieves a dynamic coordination of global exploration and local exploitation, thereby improving the overall performance of the algorithm.

The pseudocode for the selection process of the four behaviors in the adaptive behavior selection mechanism is presented in Algorithm 1.

Algorithm 1. Pseudocode of adaptive behavior selection mechanism.

Input: Population individual $Z(t)$

Output: Updated individual $Z(t+1)$

1. If $E > 1$
 2. If $\text{rand} < P$
 3. Execute long-distance migration behavior according to Equation (35).
 4. Else
 5. Execute the burrowing behavior according to Equation (39).
 6. End
 7. Else
 8. If $\text{rand} > P$
 9. Execute the foraging behavior according to Equation (41).
 10. Else
 11. Execute the predator evasion behavior with the neighborhood cooperation mechanism according to Equation (44).
 12. End
 13. End
-

3.8. Fast Non-Dominated Sorting and Crowding Distance Calculation

Since the agricultural machinery cooperative scheduling model established by Equation (33) is a multi-objective optimization problem, the fast non-dominated sorting and crowding distance mechanism is introduced to solve multi-objective problems using the ALA-AN. Specifically, fast non-dominated sorting is used to first divide the population hierarchically, prioritizing those with higher non-dominated ranks. The crowding distance is then used to assess the distribution of solutions in the objective space within the same non-dominated front, giving priority to solutions with a more uniform distribution. This approach greatly improves the algorithm's efficiency in addressing multi-objective optimization problems by allowing it to both preserve the variety of the Pareto front and successfully lower the chance of becoming stuck in local optima [44].

Non-dominated sorting classifies individuals in a population into different levels based on dominant relationships. The dominance relationship is defined as follows: for two solutions x_a and x_b , x_a is considered to dominate x_b if it outperforms x_b in at least one objective while being not worse in all other objectives. Through this sorting, the algorithm can give priority to the superior individuals with higher non-dominated levels and guide the population to converge to the Pareto front. Secondly, to maintain the diversity of solution set distribution in the target space, the crowding degree of each individual in the

same non-dominated layer is calculated to quantify the distribution density of its peripheral solutions.

To sum up, through the combined effect of fast non-dominated sorting and crowding distance calculation, the algorithm can take into account both the convergence and distribution of solutions in the evolution process, so as to obtain a high-quality Pareto solution set with comprehensive coverage and uniform distribution. This mechanism is central to guaranteeing the algorithm's performance in multi-objective optimization, and its effectiveness will be validated through comparative experiments in subsequent sections.

The flowchart of ALA-AN is illustrated in Figure 4.

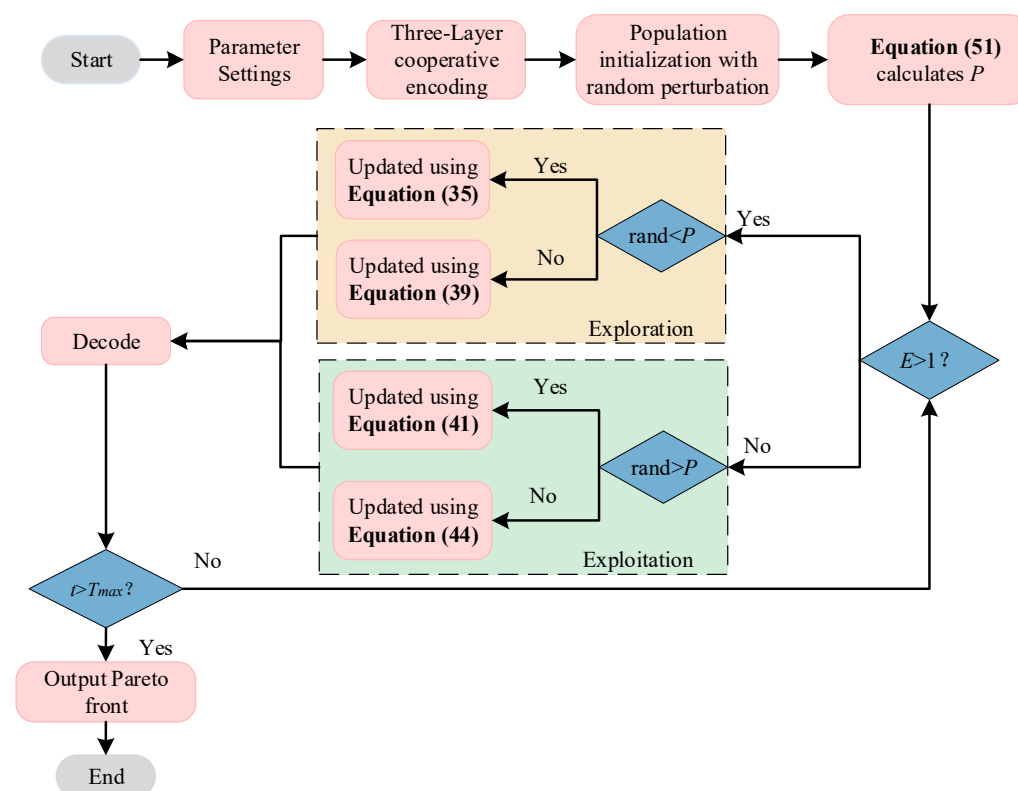


Figure 4. Flowchart of ALA-AN.

4. Experimental Setup

4.1. Benchmark Algorithms and Parameter Settings

To evaluate the adaptability and robustness of the ALA-AN under different field scales and machinery quantities, a set of comparative experiments is designed by constructing scheduling scenarios with varying problem sizes. Specifically, different combinations of the number of fields, harvesters, and grain trucks are configured to generate agricultural machinery collaboration instances with increasing complexity. This design allows assessment of the algorithm's performance in handling multi-objective scheduling problems across multiple scales and further supports comparison of solution quality under conditions where harvesting and transportation resources are relatively scarce or abundant. Five representative multi-objective optimization algorithms are selected and compared with the ALA-AN. The specific algorithms are as follows: the hybrid multi-objective ant colony optimization algorithm (HMACO) [45], the hybrid tabu-search multi-objective genetic algorithm (HTSMGA) [33], the multi-objective learning whale optimization algorithm (MLWOA) [46], the improved multi-objective particle swarm optimization algorithm (IMPSO) [47], and NSGA-II [48].

The selected benchmark algorithms are closely related to routing optimization, vehicle scheduling, and agricultural machinery scheduling problems. To ensure a fair and relevant comparison, all benchmark algorithms were adapted to the same solution representation and evaluated using the same proposed harvester–grain truck cooperative scheduling model, objective functions, constraints, input data, and termination conditions. Therefore, the experimental comparison directly reflects the effectiveness of the proposed model and ALA-AN method in solving the target cooperative scheduling problem.

For all algorithms, the population size and maximum number of iterations are set to $Np = 100$ and $T_{max} = 200$, respectively. All experiments are implemented in MATLAB 2021a on a Windows 10 workstation equipped with an AMD Ryzen 3900 12-core processor at 3.09 GHz and 31.9 GB memory. To ensure a fair comparison, all algorithms are executed on the same platform using the same termination condition and problem instances. The field locations and areas are randomly generated, and the total field area increases proportionally with the number of fields. Each algorithm is independently run 10 times for each instance.

4.2. Performance Metrics and Statistical Tests

The performance of each algorithm was evaluated from both objective-value and Pareto-front perspectives. The average total operating cost and average total carbon emissions were used to compare the economic and environmental performance of the obtained schedules. In addition, HV and IGD were used to evaluate Pareto-front quality. The Gap indicator was used to measure the relative performance difference between each benchmark algorithm and the ALA-AN. To further examine statistical significance, the Friedman test was conducted to compare the overall performance ranks of the algorithms, and the Wilcoxon signed-rank test was used for pairwise comparison between the ALA-AN and each benchmark algorithm.

The performance of each algorithm is evaluated from both objective-value and Pareto-front perspectives. The average total operating cost and average total carbon emissions are first recorded to compare the economic and environmental performance of the obtained schedules. In addition, hypervolume (HV) and inverted generational distance (IGD) are used to assess the quality of the obtained Pareto fronts [49]. HV measures the dominated objective-space volume with respect to a predefined reference point; therefore, a larger HV value indicates better convergence and diversity. IGD measures the average distance from the reference front to the approximate Pareto front, and a smaller IGD value indicates better convergence to the reference front.

To reflect the differences between the existing algorithms and the performance indicators obtained by this methodology, the following *Gap* indicators have been defined:

$$Gap = \frac{Fitness - Fitness_{ALA-AN}}{Fitness} \times 100\% \quad (52)$$

where *Fitness* represents the performance index values calculated by the existing algorithms (such as MLWOA, HTSMGA, MLWOA, IMPSO, and NSGA-II), while $Fitness_{ALA-AN}$ represents the response values calculated by the ALA-AN.

To further examine the statistical significance of the performance differences, the Friedman test is conducted on the compared algorithms, and the mean ranks are calculated for different field sizes and machinery configurations [50]. The Wilcoxon signed-rank test is then used for pairwise comparison between the ALA-AN and each benchmark algorithm based on the selected performance indicators [51].

4.3. Case-Study Data and Machinery Parameters

A real-world corn harvesting case from Jianbian Farm in Heilongjiang Province, China, was used to validate the proposed cooperative scheduling framework. The case

includes 27 corn fields to be harvested and one machinery depot. Field 0 represents the machinery depot, while fields 1–27 represent the corn fields requiring harvesting operations. The field information is provided in Table 2, and the harvester and grain truck parameters are summarized in Table 3. The spatial distribution of the selected farmland is shown in Figure 5.

Table 2. Information on the machinery depot and field operation points.

Field Number	Longitude (°)	Latitude (°)	Area (hm ²)
0	125.403892	49.916434	0
1	125.423891	49.946511	32.4
2	125.431981	49.935588	20
3	125.432174	49.94162	49.84
4	125.435414	49.917961	37.6
5	125.435414	49.947961	20
6	125.438979	49.943866	20
7	125.444648	49.948769	24.8
8	125.444648	49.926769	90
9	125.446743	49.945848	4.67
10	125.447816	49.929731	6.5
11	125.459189	49.889609	9.5
12	125.461679	49.902834	40.1
13	125.462563	49.908202	14
14	125.463438	49.935933	13
15	125.468115	49.917326	11.7
16	125.470604	49.906617	17.6
17	125.472342	49.914632	21.5
18	125.474789	49.898421	16.7
19	125.475454	49.912144	47
20	125.47909	49.901324	27
21	125.496675	49.898672	46.6
22	125.496275	49.886882	83.8
23	125.487235	49.912442	55.7
24	125.476562	49.910457	96.8
25	125.485306	49.881752	60
26	125.484533	49.885783	33.2
27	125.484365	49.876528	65

Table 3. Information on harvester and grain truck.

Harvester Information		Grain Truck Information	
Operational efficiency	3.6 (hm ² ·h ^{−1})	Travel speed	40 (km·h ^{−1})
Travel speed	20 (km·h ^{−1})	Granary capacity	40 (m ³)
Grain tank capacity	10 (m ³)	Travel fuel consumption rate	7.5 (L·hm ^{−2})
Operating fuel consumption rate	52 (L·hm ^{−2})	Carbon emissions per unit travel distance	20 (kgCO ₂ ·km ^{−1})
Travel fuel consumption rate	3.75 (L·km ^{−1})	Unloading time	0.2 (h)
Carbon emissions per unit travel distance	25 (kgCO ₂ ·km ^{−1})	Waiting penalty cost	20 (Yuan·h ^{−1})
Carbon emissions per unit operating distance	17.9 (kgCO ₂ ·km ^{−1})	Diesel price	7.5 (Yuan·L ^{−1})



Figure 5. Overview of selecting experimental farmland. The red shaded area indicates the boundary and spatial extent of the farmland selected for the field experiment.

5. Results and Discussion

5.1. Comparative Results Under Different Problem Scales

The comparative results of the six algorithms under different problem scales are reported in Tables 4–6 and Figures 6–9. Table 4 presents the average total cost and total carbon emissions obtained under different field sizes and machinery configurations, and Figure 6 provides a graphical comparison of these two objectives. Table 5 further reports the relative performance *Gap* of the benchmark algorithms compared with the ALA-AN, which are visualized in Figure 7. Table 6 and Figure 8 compare the Pareto-front quality of the algorithms using HV and IGD indicators. Finally, Figure 9 and Table 7 present the Friedman mean-rank results and Wilcoxon signed-rank test results, respectively.

Table 4. Average total cost and total carbon emissions for different-scale collaborative scheduling.

Field Number	Harvester Number	Truck Number	ALA-AN		HMACO		HTSMGA		MLWOA		IMPSO		NSGA-II	
			Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions
15	2	3	4714.53	4345.49	4714.53	4345.49	4714.53	4345.49	4714.53	4345.49	4714.53	4345.49	4714.53	4345.49
	3	4	5945.26	5494.56	6055.87	5579.62	5945.26	5494.56	6072.85	5607.52	6332.05	5894.24	6048.54	5582.22
	4	5	7115.09	6597.92	7207.63	6695.57	7252.53	6764.93	7439.14	6854.49	7645.21	7089.62	7230.82	6673.96
30	3	4	7431.41	6849.61	7465.82	6871.06	7807.24	7180.37	8405.60	7730.84	8536.94	7817.90	7462.10	6905.33
	4	5	8832.71	8180.00	8933.44	8256.63	9268.39	8595.67	9943.67	9207.53	10,362.68	9584.50	8560.98	7953.35
	5	6	10,211.17	9476.02	10,152.74	9496.19	10,693.39	9987.81	10,850.30	10,132.30	11,843.51	11,016.71	10,395.47	9905.54
80	3	4	10,174.79	9279.00	10,313.34	9336.99	11,187.85	10,239.23	11,157.49	10,155.87	12,016.93	10,936.34	10,519.81	9498.21
	5	6	13,400.62	12,359.98	13,150.39	12,166.87	14,883.19	13,679.34	15,354.03	14,118.52	16,494.17	15,258.07	13,874.29	12,731.71
	8	10	17,926.90	16,551.03	18,437.62	17,108.12	19,545.46	18,120.39	20,938.85	19,351.86	21,775.91	20,158.26	18,533.16	17,130.03

Table 4 shows that the differences among the algorithms become more evident as the number of fields, harvesters, and grain trucks increases. Across different scheduling instances, the ALA-AN generally obtains the lowest or near-lowest total cost and carbon emissions, indicating good adaptability to different problem scales. The HMACO and HTSMGA also show competitive performance in some instances, whereas the MLWOA and IMPSO perform less effectively, especially in large-scale scenarios. For the instance with 80 fields, 8 harvesters, and 10 grain trucks, the ALA-AN obtains the lowest total cost and carbon emissions, with values of 17,926.90 and 16,551.03, respectively. This indicates that the proposed algorithm has stronger search capability and coordination ability when the harvesting–transportation scheduling problem becomes more complex.

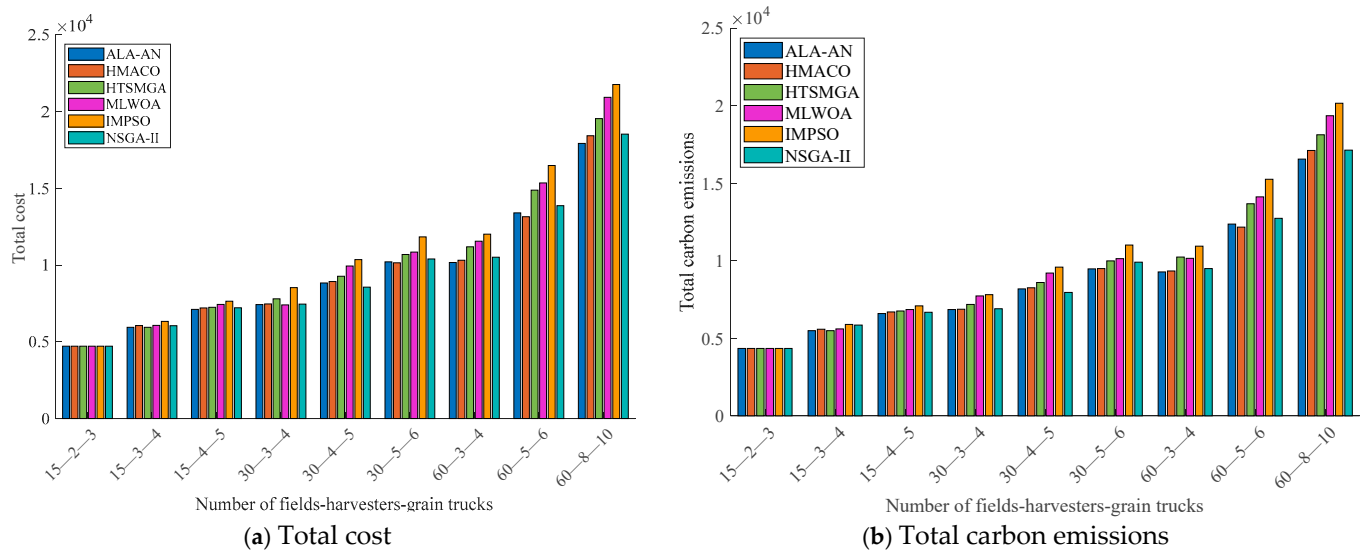


Figure 6. Comparison of optimization objectives under different problem scales.

Figure 6 provides a more intuitive comparison of the results in Table 4. As shown in Figure 6a, the total cost increases with the expansion of the scheduling scale, but the ALA-AN maintains a clear advantage in most medium- and large-scale instances. A similar pattern can be observed in Figure 6b for carbon emissions. This suggests that the proposed method can reduce operating costs while maintaining good environmental performance.

Table 5. Relative performance *Gap* (%) in total cost and carbon emissions compared with ALA-AN.

Field Number	Harvester Number	Truck Number	HMAO		HTSMGA		MLWOA		IMPSO		NSGA-II	
			Total		Total		Total		Total		Total	
			Total Cost	Carbon Emissions	Total Cost	Carbon Emissions	Total Cost	Carbon Emissions	Total Cost	Carbon Emissions	Total Cost	Carbon Emissions
15	2	3	0	0	0	0	0	0	0	0	0	0
	3	4	1.83	1.52	0.00	0.00	2.10	2.01	6.11	6.78	1.71	1.57
	4	5	1.28	1.46	1.90	2.47	4.36	3.74	6.93	6.94	1.60	1.14
30	3	4	0.46	0.31	4.81	4.61	11.59	11.40	12.95	12.39	0.41	0.81
	4	5	1.13	0.93	4.70	4.84	11.17	11.16	14.76	14.65	−3.17	−2.85
	5	6	0.41	0.21	4.51	5.12	5.89	6.48	13.78	13.99	1.77	4.34
80	3	4	1.34	0.62	9.06	9.38	8.81	8.63	15.33	15.15	3.28	2.31
	5	6	1.11	0.86	9.96	9.64	12.72	12.46	18.76	18.99	3.41	2.92
	8	10	2.77	3.26	8.28	8.66	14.38	14.47	17.68	17.89	3.27	3.38

Table 5 presents the relative gaps between the benchmark algorithms and ALA-AN. Larger positive *Gap* values indicate greater performance differences from the ALA-AN. The results show that the performance gaps generally increase as the problem scale becomes larger, which means that the advantage of the ALA-AN is more pronounced in complex scheduling scenarios. For small-scale instances, some benchmark algorithms such as the HMAO and NSGA-II achieve relatively close results. However, for medium- and large-scale instances, the MLWOA and IMPSO show substantially larger gaps in both cost and carbon emissions.

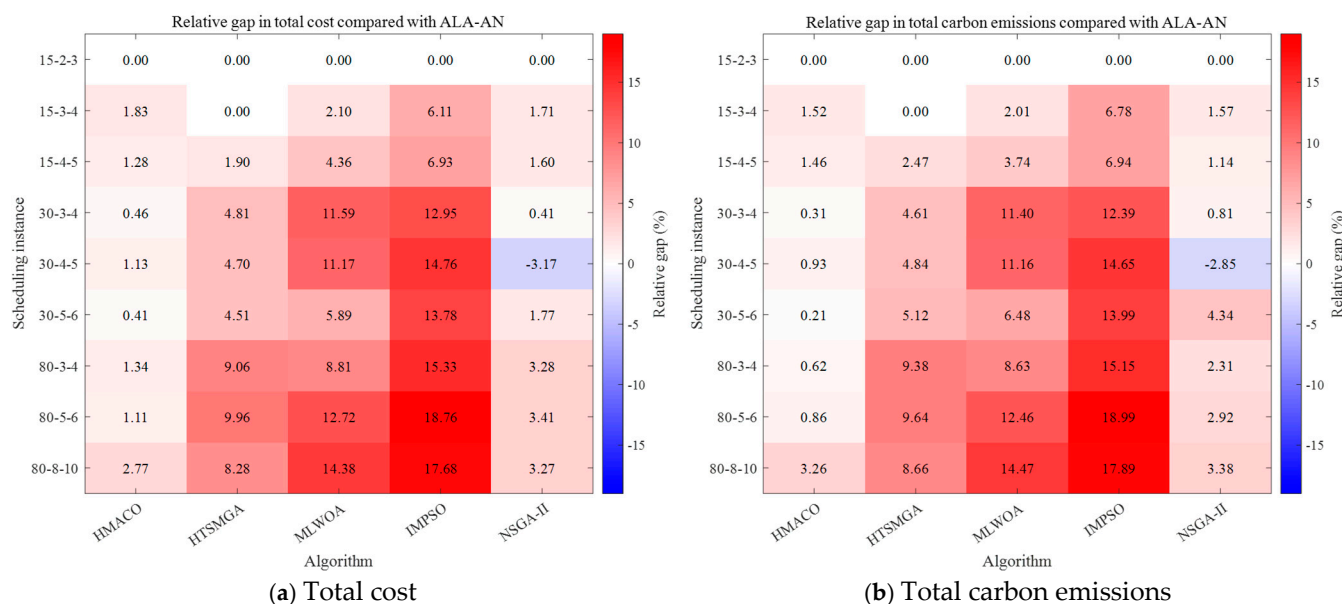


Figure 7. Heatmap of relative performance gaps in total cost and carbon emissions compared with ALA-AN.

Figure 7 visualizes the relative gaps reported in Table 5. The heatmaps show that most cells are positive, indicating that the ALA-AN outperforms the benchmark algorithms in most scheduling instances. The darker regions mainly appear in medium- and large-scale cases, especially for the MLWOA and IMPSO, which further confirms that the proposed algorithm has better scalability for large-scale cooperative harvesting and transportation scheduling.

Table 6. HV and IGD for different-scale collaborative scheduling.

Field Number	Harvester Number	Truck Number	ALA-AN		HMACO		HTSMGA		MLWOA		IMPSO		NSGA-II	
			IGD	HV	IGD	HV	IGD	HV	IGD	HV	IGD	HV	IGD	HV
15	2	3	0.0265	0.9459	0.0551	0.8011	0.0598	0.8151	0.0698	0.7264	0.0697	0.8932	0.0364	0.9120
	3	4	0.0490	0.8954	0.0642	0.8548	0.0254	0.8853	0.0367	0.8569	0.0587	0.7631	0.0528	0.8905
	4	5	0.0322	0.9023	0.0483	0.8551	0.0694	0.7635	0.0428	0.8864	0.0415	0.8963	0.0489	0.8887
30	3	4	0.0265	0.9647	0.0639	0.7667	0.0528	0.8967	0.0561	0.8682	0.0591	0.9104	0.0681	0.7346
	4	5	0.0252	0.9524	0.0846	0.7783	0.0538	0.7648	0.0753	0.7587	0.0938	0.4982	0.0528	0.7730
	5	6	0.0585	0.8885	0.0658	0.6742	0.0431	0.8803	0.0594	0.8961	0.0494	0.8232	0.0867	0.7261
80	3	4	0.0582	0.8982	0.0891	0.6043	0.0813	0.7632	0.0827	0.7264	0.0896	0.7041	0.0457	0.8698
	5	6	0.0588	0.8817	0.0823	0.7681	0.0827	0.7276	0.0918	0.7834	0.0628	0.7858	0.0866	0.8359
	8	10	0.0529	0.8343	0.0897	0.6407	0.0753	0.8417	0.0729	0.7273	0.0967	0.8647	0.0898	0.8444

Table 6 presents the HV and IGD results of the six algorithms under different problem scales. Overall, the ALA-AN achieves the most consistent performance, obtaining higher HV values and lower or competitive IGD values in most instances. This indicates that the Pareto fronts generated by the ALA-AN generally have better convergence and diversity than those of the benchmark algorithms. While some benchmark algorithms perform better on individual instances, their performance lacks consistency across different scales, highlighting sensitivity to problem size and configuration. In contrast, the ALA-AN maintains stable Pareto-front quality as the number of fields and machines increases, demonstrating the effectiveness of the three-layer cooperative representation and neighborhood-cooperative search mechanism. These results suggest that the ALA-AN provides robust and high-quality solutions for coupled routing and synchronization decisions in large-scale agricultural logistics, supporting both operational efficiency and sustainability.

objectives. Figure 8 further illustrates the HV and IGD trends. The ALA-AN maintains relatively stable performance as the scheduling scale increases, whereas several benchmark algorithms show larger fluctuations. This result indicates that the three-layer encoding structure and neighborhood cooperation mechanism help improve the robustness of Pareto-front search in coupled harvester–grain truck scheduling.

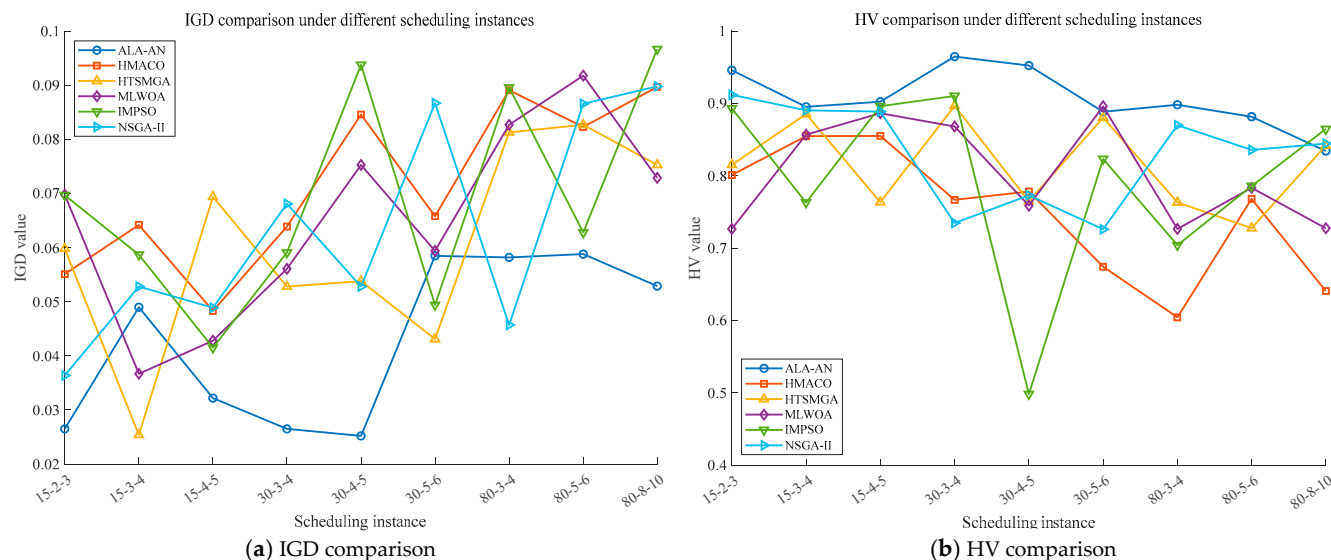


Figure 8. Pareto-front quality comparison of different algorithms based on IGD and HV.

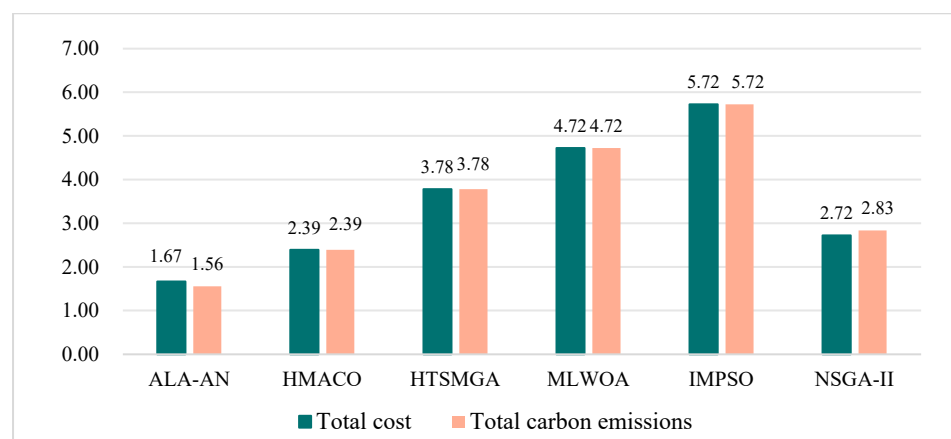


Figure 9. Friedman mean-rank results for different site sizes and mechanical configurations.

Table 7. The Wilcoxon test results of the two indicators under different numbers of fields.

<i>p</i> -Value	Total Cost	Total Carbon Emissions
15	0.1318	0.1318
30	0.0193	0.0165
80	0.0142	0.0142

From the Friedman mean-rank results shown in Figure 9, the ALA-AN obtains the smallest average rank for both total cost and carbon emissions, indicating the best overall performance among the compared algorithms. The HMAO ranks second, while NSGA-II shows moderate performance. The HTSMGA, MLWOA, and IMPSO have relatively larger average ranks, suggesting weaker overall competitiveness.

The Wilcoxon test results reported in Table 7 further confirm these findings. For 30 and 80 fields, the ALA-AN demonstrates statistically significant improvements over HMAO and the other benchmark algorithms ($p < 0.05$). In contrast, no significant differ-

ences are observed for the 15-field instances, where the coordination complexity remains relatively low and most algorithms can obtain comparable solutions. As the problem scale increases, however, the performance advantage of the ALA-AN becomes increasingly evident, highlighting its effectiveness in handling complex harvesting–transportation synchronization decisions.

Overall, the statistical results confirm that the ALA-AN provides robust and scalable performance across different scheduling scenarios, making it suitable for large-scale cooperative harvesting and transportation scheduling.

5.2. Ablation Experiment

To verify the contribution of the proposed improvement strategies to the performance of the ALA-AN, this section designs a set of ablation experiments to systematically evaluate the effectiveness of each improvement module. Specifically, we compare the ALA-AN with the following four variants:

- (1) ALA: Standard artificial lemming algorithm.
- (2) ALA1: ALA + a three-layer collaborative encoding structure based on ascending index mapping.
- (3) ALA2: ALA1 + population initialization combining K-means clustering with random perturbation strategy.
- (4) ALA3: ALA2 + adaptive behavior selection mechanism.
- (5) ALA-AN: ALA3+ the predator-avoidance phase updating formula based on the neighborhood cooperation mechanism

The experimental settings are consistent with those in Section 4.1: the population size is set to 100, the maximum number of iterations is 200, and each algorithm is independently run 10 times on each instance. Six scheduling scenarios of different scales, identical to those in Table 4, are adopted. The comparison results in terms of total operating cost and carbon emissions are presented in Table 8 under different problem scales.

Table 8. Average total cost and total carbon emissions for each variant.

Field Number	Harvester Number	Truck Number	ALA-AN		ALA3		ALA2		ALA1		ALA	
			Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions
15	2	3	4714.53	4345.49	4714.53	4345.49	5036.99	5239.23	5207.63	6252.53	5207.53	5804.95
	3	4	5945.26	5494.56	5994.56	5607.52	6194.24	6582.22	6252.53	6339.14	6245.21	6730.82
	4	5	7115.09	6597.92	7201.31	6645.46	7355.51	7077.11	7507.24	8405.60	7536.94	8462.10
30	3	4	7431.41	6849.61	7451.99	6885.40	7640.17	7121.00	7720.13	7445.46	7790.67	7708.22
	4	5	8832.71	8180.00	8923.61	8213.73	9033.81	8640.56	9148.21	8853.97	9240.17	8874.34
	5	6	10,211.17	9476.02	10,781.89	9645.57	14,066.94	9705.63	14,573.35	9877.51	14,533.64	9875.48
80	3	4	10,174.79	9279.00	10,185.34	9385.69	10,316.68	9733.69	10,269.69	10,156.42	10,275.06	10,347.38
	5	6	13,400.62	12,359.98	13,586.44	12,979.53	14,129.32	14,077.17	14,702.00	14,292.68	14,828.45	14,356.09
	8	10	17,926.90	16,551.03	17,961.67	17,082.84	18,002.76	17,273.11	18,158.92	17,300.98	18,161.97	17,308.12

As shown in Table 8, the full ALA-AN consistently achieves the lowest total operating cost and carbon emissions across most instances. While ALA3 performs comparably to the ALA-AN in small-scale scenarios, the performance gap widens as problem complexity increases, highlighting the importance of the full set of enhancements for large-scale cooperative scheduling. This result indicates that the three-layer encoding structure plays a crucial role in maintaining solution feasibility and establishing the collaborative mapping among fields, harvesters, and grain trucks. The original continuous encoding scheme tends to generate infeasible solutions when decoded into integer scheduling plans and is ineffective in representing the complex coordination constraints among multiple machines, thereby significantly reducing search efficiency. The adaptive behavior selec-

tion mechanism dynamically balances exploration and exploitation, playing a key role in medium and large-scale problems. The hybrid initialization strategy provides high-quality initial solutions for the search process, while the neighborhood cooperation mechanism further improves solution quality through refined local search.

The ablation study demonstrates that each improvement module plays a distinct role in enhancing algorithmic performance. The synergistic combination of these strategies enables the ALA-AN to deliver robust, scalable, and high-quality solutions for multi-objective agricultural machinery collaborative scheduling, supporting both economic and environmental objectives in practical logistics operations.

To further evaluate the statistical significance of the results, a Friedman test was conducted based on the average ranks of all algorithms. Table 9 presents the chi-square test results for the ALA-AN and its variants, while Figure 10 shows the corresponding Friedman mean-rank results for the different variants.

Table 9. Friedman test χ^2 results for different site sizes and mechanical configurations.

Objective	k	α	χ^2	$\chi^2_{\alpha}[k-1]$	H_0	H_1
Total cost	5	0.05	32.07	11.070	Reject	Accept
Total carbon emissions	5	0.05	33.68	11.070	Reject	Accept

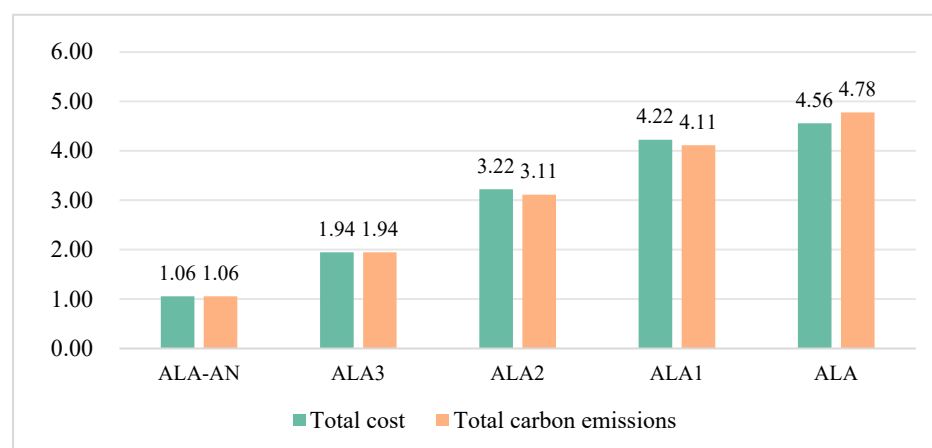


Figure 10. The Friedmann average rank results of the ALA-AN and its different variants.

As shown in Table 9, under the significance level of $\alpha = 0.05$, the Friedman test statistics for total cost and total carbon emissions are 32.07 and 33.68, respectively, both of which are significantly larger than the critical value 9.49. Therefore, the null hypothesis H_0 is rejected, and the alternative hypothesis H_1 is accepted, indicating that the performance differences among the ALA-AN and its variants are statistically significant. This demonstrates that the introduced improvement strategies have substantial effects on algorithmic performance. Furthermore, the Friedman test results presented in Figure 10 reveal that the ALA-AN consistently attained the highest average rank across both target tasks, whereas its variants exhibited progressively lower average ranks. These results confirm that the proposed improvement strategies effectively enhance the search capability and solution quality of the original algorithm.

5.3. Experimental Results of the Case Study

Based on the case-study data and machinery parameters described in Section 4.3, the ALA-AN and five benchmark algorithms were applied to the Jianbian Farm instance. The experimental settings are consistent across all algorithms. The case study involves four combined harvesters and five grain trucks (see Table 3 for the corresponding parameters),

and all harvesting tasks are required to be completed within 10 days. Each algorithm is independently executed 10 times under the same termination conditions. For each run, the obtained objective values—total operating cost and total carbon emissions—are recorded, and the results from the 10 runs are summarized. Table 10 reports on the statistical results and corresponding average performance of all algorithms during 10 independent runs.

Table 10. Statistical results of different algorithms for solving farmland instance.

Algo-rithms	ALA-AN		HMACO		HTSMGA		MLWOA		IMPISO		NSGA-II	
No	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions	Total Cost	Total Carbon Emissions
1	20,230.88	11,432.3	20,250.11	11,440.72	20,268.90	11,454.66	20,240.79	11,435.86	20,309.00	11,474.99	20,262.18	11,448.37
2	20,248.11	11,439.62	20,238.70	11,434.45	20,319.90	11,479.21	20,286.51	11,462.23	20,297.88	11,465.49	20,244.61	11,440.25
3	20,243.73	11,438.53	20,246.63	11,439.61	20,288.72	11,465.08	20,301.81	11,475.91	20,299.98	11,470.15	20,243.07	11,437.71
4	20,246.63	11,439.61	20,247.54	11,442.87	20,288.95	11,464.25	20,266.40	11,452.34	20,288.46	11,467.28	20,242.82	11,439.44
5	20,243.88	11,439.89	20,238.06	11,437.31	20,290.54	11,467.74	20,269.54	11,452.52	20,287.24	11,464.80	20,240.41	11,436.41
6	20,237.51	11,435.68	20,248.12	11,441.11	20,284.52	11,460.34	20,268.13	11,454.14	20,303.70	11,473.86	20,250.15	11,451.34
7	20,240.61	11,438.83	20,250.04	11,442.99	20,268.90	11,454.66	20,271.01	11,456.88	20,272.61	11,452.81	20,242.30	11,438.55
8	20,238.84	11,438.28	20,243.38	11,437.90	20,319.90	11,479.21	20,254.75	11,445.98	20,286.24	11,466.37	20,243.07	11,437.71
9	20,243.61	11,438.32	20,255.35	11,445.43	20,288.72	11,465.08	20,268.10	11,452.74	20,281.43	11,460.19	20,243.07	11,437.71
10	20,244.79	11,438.89	20,238.51	11,435.89	20,288.95	11,464.25	20,267.41	11,452.07	20,277.12	11,456.33	20,240.41	11,446.41
Average	20,241.86	11,438.00	20,245.64	11,439.83	20,290.80	11,465.45	20,269.45	11,454.07	20,290.37	11,465.23	20,245.21	11,441.39

According to Table 10, the ALA-AN achieves the best performance across the 10 independent runs for both optimization objectives: total cost and total carbon emissions. Moreover, it attains the lowest average total cost and the lowest average carbon emissions, demonstrating its superior overall performance in solving the multi-objective cooperative scheduling problem for harvesters and grain trucks. In multiple independent experiments, the ALA-AN has the lowest total cost and carbon emissions, which fully shows its excellent comprehensive optimization ability. Although the results of the five comparison algorithms are similar to those of the ALA-AN in several runs, they usually exhibited the problem of high total cost or high total carbon emissions. For instance, while the HMACO achieved lower carbon emissions in a few cases, its total cost is notably higher than that of the ALA-AN. The MLWOA, IMPISO, and NSGA-II show higher carbon emissions or higher total costs in multiple runs. It is worth emphasizing that the ALA-AN shows a remarkable advantage in multi-objective balance and global research. It successfully minimizes scheduling costs and effectively combines carbon emission control. To intuitively compare the robustness of the six algorithms, the standard deviation of the total cost and total carbon emissions of the six algorithms in 10 runs is shown in Figure 11.

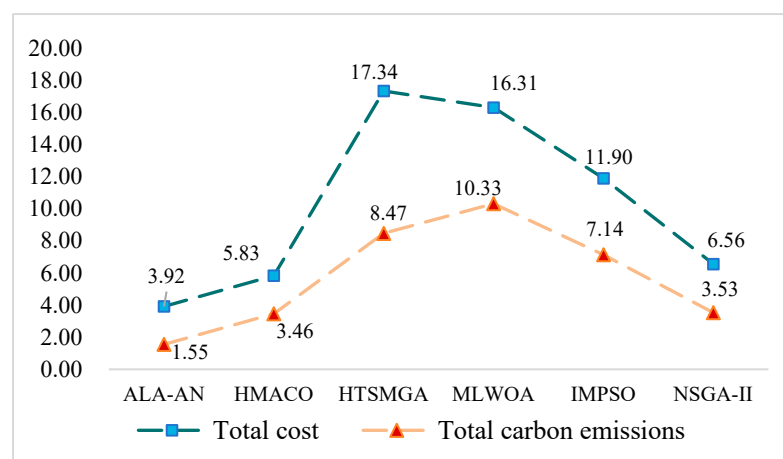


Figure 11. Standard deviation line chart of total cost and total carbon emissions for farmland instance.

As can be seen from Figure 11, the standard deviation of the total cost and total carbon emissions of the ALA-AN is the smallest among the six algorithms, which are 3.92 and 1.55 respectively, indicating that the ALA-AN has better stability and robustness. In addition, the MLWOA has the lowest stability and the largest standard deviation of total cost and total carbon emissions, which indicates that its solution is highly volatile and prone to randomness. Between these two extremes lies the robustness of the HMACO, HTSMGA, IMPSO and NSGA-II. The standard deviation of the total cost of IMPSO and NSGA-II is relatively small, showing relative stability. The standard deviation of the total cost and total carbon emissions of the HMACO is relatively small, demonstrating high stability.

To further illustrate the distribution and stability of different algorithms over 10 independent runs, boxplots of total cost and total carbon emissions are presented. As shown in Figure 12, the ALA-AN consistently produces the lowest total cost and total carbon emissions among all compared algorithms. In addition, its relatively compact box and short whiskers indicate small performance fluctuations across repeated runs, demonstrating good robustness. The HMACO and NSGA-II also achieve competitive results and outperform the HTSMGA, MLWOA, and IMPSO overall. By contrast, the HTSMGA and IMPSO show higher medians and wider distributions, suggesting inferior solution quality and weaker stability.

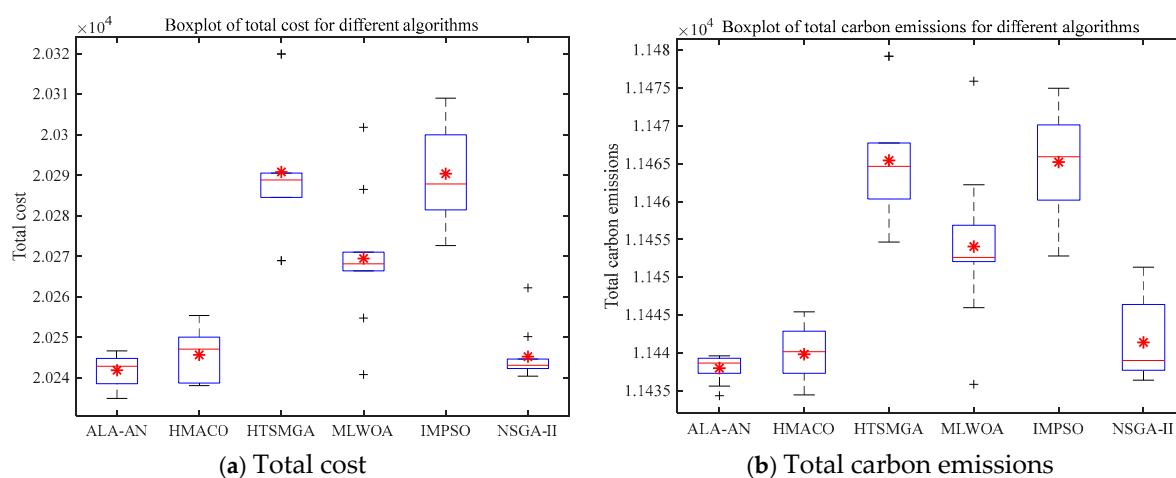


Figure 12. Boxplot of total cost and total carbon emissions for different algorithms.

Furthermore, the Friedman test was performed on the two optimization objectives, total operating cost and total carbon emissions, to further assess if the reported performance differences among the evaluated algorithms are statistically significant. The results obtained from the 10 independent runs are treated as blocks in the Friedman test. Table 11 reports the Friedman mean ranks of each algorithm for both objectives, while Table 12 summarizes the corresponding Friedman test statistics and hypothesis testing results at the 0.05 significance level.

Table 11. Total cost and carbon emissions of different algorithms Friedman mean rank.

Algorithm	Total Cost	Total Carbon Emissions
ALA-AN	1.8	1.9
HMACO	2.3	2.3
HTSMGA	5.4	5.4

MLWOA	4.1	4.2
IMPSO	5.3	5.2
NSGA-II	2.1	2

Table 12. Friedman test χ^2 results for different objectives.

Objective	k	α	χ^2	$\chi^2_{\alpha}[k-1]$	H_0	H_1
Total cost	6	0.05	38.75	11.070	Reject	Accept
Total carbon emissions	6	0.05	37.83	11.070	Reject	Accept

As shown by the Friedman mean ranks in Table 11, the ALA-AN achieves the first rank for both total operating cost and total carbon emissions, indicating the best overall performance among the compared algorithms. The HMAO and NSGA-II rank second and third, respectively, and also demonstrate competitive performance. In contrast, the HTSMGA, IMPSO, and MLWOA obtain relatively higher mean ranks for both objectives, suggesting weaker overall performance under the current problem settings.

The Friedman test results reported in Table 12 indicate that the performance differences among the compared algorithms are statistically significant for both optimization objectives. Since six algorithms are compared in this study, $k = 6$, $k - 1 = 5$, and when $\alpha = 0.05$, according to the chi square distribution table, the value of $\chi^2_{\alpha}[k - 1]$ is 11.070. The calculated chi-square values for total operating cost and total carbon emissions are 38.75 and 37.83, respectively, both of which are much larger than the critical value. Therefore, the null hypothesis H_0 , which assumes no significant performance difference among the algorithms, is rejected for both objectives. These results confirm that the observed performance differences are not caused by random fluctuations. Together with the Friedman mean-rank results in Table 11, this analysis further verifies the effectiveness and robustness of the proposed ALA-AN in solving the multi-objective agricultural machinery co-operative scheduling problem.

Although statistical tests confirm that there are significant differences in the overall performance of the algorithm, these results cannot reveal the convergence speed of each method or the stability of the search in the iterative process. Figure 13 shows the convergence curve of total cost and total carbon emissions.

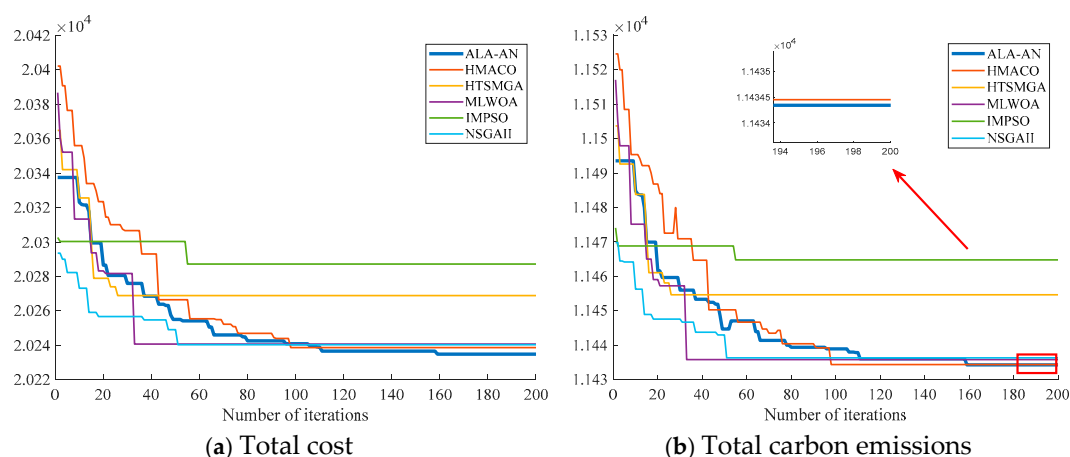


Figure 13. Convergence curves of the six algorithms for solving the instance.

According to Figure 13, all six algorithms' objective values decrease and then plateau, indicating solution improvements. However, obvious differences appear in both convergence speed and the final solution quality. In Figure 13a, the ALA-AN drops rapidly at the early stage and then continues to improve steadily, showing small fluctuations in the

mid-to-late iterations. This behavior indicates good stability and sustained search capability, and the final cost reached by the ALA-AN is lower than those obtained by the five competing methods. By contrast, IMPSO and the HTSMGA show an early plateau, which limits subsequent improvements and leads to inferior results. A similar pattern is observed for carbon emissions in Figure 13b. The ALA-AN converges faster and achieves a better final emission level. As indicated by the red arrow, the inset provides an enlarged view of the red-boxed region during the final iterations, allowing the slight differences in the final carbon emission values of the algorithms to be observed more clearly. The HMAO exhibits partial improvements in certain phases, but its search tends to stagnate in the later iterations. It is also worth noting that the ALA-AN ends with slightly lower emissions than the HMAO, highlighting its advantage when carbon mitigation is emphasized in agricultural machinery scheduling. Overall, across both objectives, the ALA-AN demonstrates faster convergence, higher final accuracy, and stronger stability. These characteristics suggest that the ALA-AN can maintain an effective balance between exploration and exploitation and handle the trade-off between cost and emissions more reliably.

Based on the above convergence observations, the ALA-AN shows stable and efficient optimization behavior on the Jianbian Farm instance. To further evaluate the quality and spread of the non-dominated solutions under the multi-objective setting, the Pareto front obtained by the ALA-AN is reported next. Representative solutions are then selected from the Pareto set to visualize the corresponding harvester and grain truck routing plans, offering a more intuitive view of the cooperative scheduling outcomes. The Pareto front obtained by solving the multi-objective cooperative scheduling problem for agricultural machinery in the farm using the ALA-AN is illustrated in Figure 14. In this figure, the x -axis represents the total cost of the harvesting operation, while the y -axis represents the total carbon emissions generated during the operation process. To demonstrate the details of the scheduling solution, the individual with the optimal fitness is selected. Figures 15 and 16 show the corresponding travel routes for combining harvesters and grain trucks separately. Table 13 provides the specific operation paths for each harvester and grain truck, as well as the total cost and total carbon emissions corresponding to the scheduling scheme. The agricultural machinery depot, denoted by label “0” in the figure, is where all agricultural machines begin, finish their operational tasks one after the other, and then return to this depot. The labels “1–27” stand for the 27 corn fields that are ready for harvest. The harvester number is signified by h_i . The grain truck number is represented by c_j .

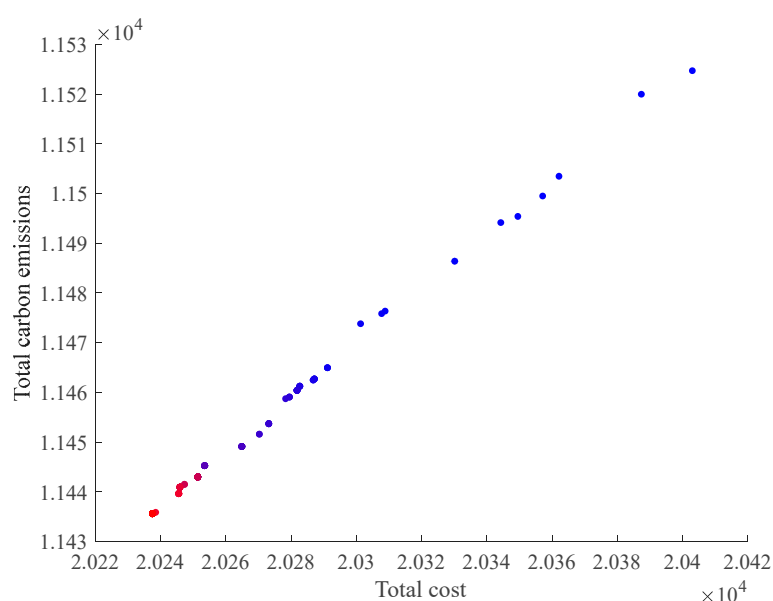


Figure 14. Pareto front of the ALA-AN-based scheduling scheme.

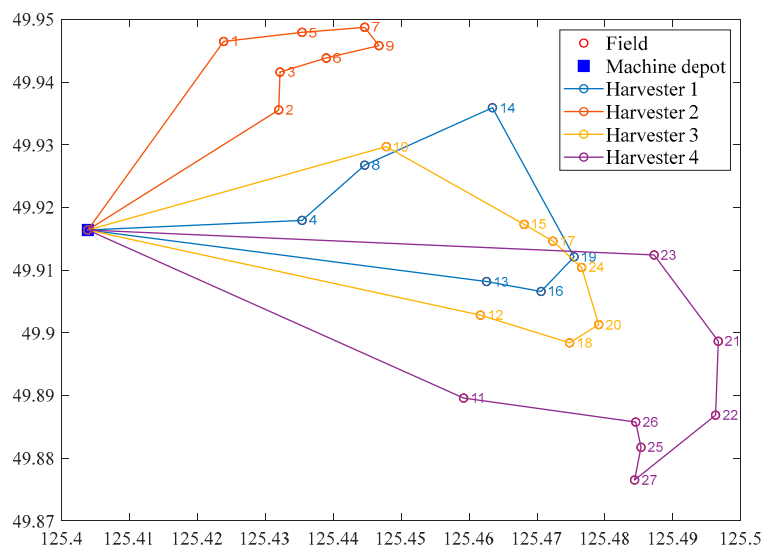


Figure 15. Optimal routes of each harvester.

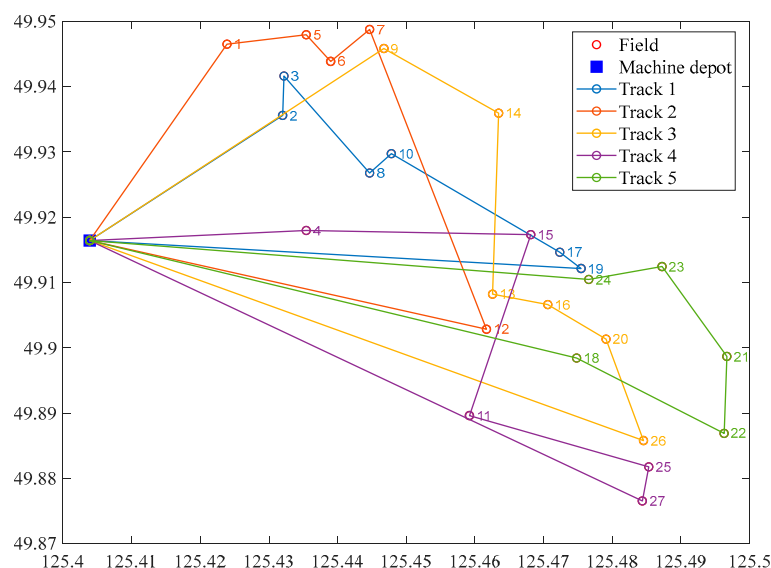


Figure 16. Optimal routes of each grain truck.

Table 13. Driving routes and corresponding total cost and carbon emissions of harvesters and grain trucks.

Number	Route	Travel Distance (km) (Harvested Area, hm ²)	Total Cost (Yuan)	Total Carbon Emissions (kgCO ₂ km ⁻¹)
Harvester h_1	0→4→8→14→19→16→13→0	508.17 (219.20)	3320.11	1660.06
Harvester h_2	0→2→3→6→9→7→5→1→0	472.89 (171.71)	2598.30	1299.15
Harvester h_3	0→10→15→17→24→20→18→12→0	515.23 (220.30)	3335.43	1667.71
Harvester h_4	0→11→26→25→27→22→21→23→0	483.61 (353.80)	5333.38	2666.69
Grain truck c_1	0→2→3→8→10→17→19→0	316.20	610.55	447.74
Grain truck c_2	0→1→5→6→7→12→0	266.06	1672.85	1226.76
Grain truck c_3	0→9→14→13→16→20→26→0	329.90	2128.52	1560.91
Grain truck c_4	0→4→15→11→25→27→0	297.47	617.05	452.51
Grain truck c_5	0→24→23→21→22→18→0	261.49	614.69	450.77
Total			20,230.88	11,432.30

According to the data in Table 13, the four harvesters completed a total harvest area of 965.01 hm², covering all 27 designated corn fields. The harvesting areas of the four harvesters are 219.20 hm², 171.71 hm², 220.30 hm², and 353.80 hm², respectively. Although there are significant differences in the operating load between different harvesters, the core goal of the scheduling problem was to minimize the total system cost and total carbon emissions, rather than to pursue the balanced allocation of tasks for each single device. As indicated in Figure 15, if harvesters h_1 and h_2 are forcibly allocated to the operation areas covered by h_4 to balance the load, the resulting cross-regional transfer will inevitably lead to additional fuel consumption, thereby increasing the total cost and total carbon emissions of the system. Therefore, h_4 undertakes more tasks in the current scheduling, which is based on the geographical characteristics of its service package in the spatial distribution. This strategy minimizes the total idle and transition distance of agricultural machinery at the system level, fundamentally realizes the coordinated reduction of overall energy consumption and carbon emissions.

Figure 16 illustrates the service sequence of the grain trucks in the fields. The spatial distribution of grain truck service areas exhibits clear zonal characteristics, forming a radial service range centered on grain depots. There are notable variations in transit efficiency even though the five grain trucks are dispersed across comparatively distinct geographical areas. The c_2 and c_3 service fields are more dispersed, resulting in frequent path detours and returns. This results in longer waiting times and longer non-productive travel distances, which raises unit transportation costs and carbon emissions. In contrast, c_1 , c_4 , and c_5 operate mainly in field clusters with spatial concentration. These trucks can maintain lower operating costs and fewer emissions since their transport routes are more direct and compact. This phenomenon shows that the transport efficiency of grain trucks not only depends on the driving distance but is also affected by several coupling factors, including the spatial continuity of the field, the task density, and the degree of coordination with the harvester.

The goal of the scheduling method proposed in this paper is to achieve the global optimal performance of the whole system under the conditions of cooperative harvesting and transportation, rather than the load balance of a single harvester or grain truck. Facing multiple practical constraints such as decentralized field distribution, complex operation sequence, and vehicle space–time coordination, this model achieves a dynamic balance between local trade-offs and overall optimality while balancing the total cost and total carbon emission targets. It can provide a reasonable and effective optimization solution for complex agricultural machinery collaborative scheduling problems that can both reduce costs and control carbon emissions.

5.4. Practical Implications and Sensitivity Analysis

The results above show that the proposed ALA-AN method can obtain lower total operating cost and carbon emissions than the compared algorithms. From a practical perspective, these improvements indicate that the optimized schedule can reduce unnecessary machinery movement, improve the coordination between harvesters and grain trucks, and decrease fuel-related emissions during harvesting operations. Therefore, the value of the proposed model is not limited to algorithmic performance; it can also support field managers in organizing harvesting sequences, assigning machines, and coordinating grain transportation more efficiently.

To further examine the influence of key input parameters, a sensitivity analysis was conducted using the Jianbian Farm case. Five parameters were considered: diesel price P_f , weather-adjusted operational efficiency $\bar{W}_t$, harvester grain tank capacity V_h^{max} , grain truck capacity Q_c , and crop yield ρ_i . Each parameter was varied by −20%, −10%, 0%, 10%, and 20%, while the other parameters remained unchanged. The 0% case was used as the

baseline. The percentage changes in total cost and carbon emissions were calculated relative to the baseline scenario, as shown in Table 14.

Table 14. Sensitivity analysis results for the Jianbian Farm case under different parameter settings.

Parameter	Variation (%)	Total Cost	Cost Change (%)	Carbon Emissions	Emission Change (%)
Diesel price P_f	−20	15,167.23	−25.07	11,438.16	0
	−10	17,063.90	−15.7	11,436.83	−0.01
	0	20,241.86	0	11,438	0
	10	20,855.19	3.03	11,436.82	−0.01
	20	22,750.85	12.4	11,438.59	0.01
Weather-adjusted efficiency $\bar{W}_t$	−20	22,506.92	11.19	12,270.69	7.28
	−10	21,253.95	5	11,895.52	4
	0	20,241.86	0	11,438	0
	10	17,669.12	−12.71	9851.55	−13.87
	20	16,594.28	−18.02	9313.96	−18.57
Harvester grain tank capacity V_h^{max}	−20	21,011.05	3.8	11,792.58	3.1
	−10	20,585.97	1.7	11,598.13	1.4
	0	20,241.86	0	11,438	0
	10	19,998.96	−1.2	11,323.62	−1
	20	19,837.02	−2	11,243.55	−1.7
Grain truck capacity Q_c	−20	21,294.44	5.2	11,964.15	4.6
	−10	20,727.66	2.4	11,666.76	2
	0	20,241.86	0	11,438	0
	10	19,877.51	−1.8	11,254.99	−1.6
	20	19,594.12	−3.2	11,117.74	−2.8
Crop yield ρ_i	−20	19,330.98	−4.5	10,957.6	−4.2
	−10	19,816.78	−2.1	11,220.68	−1.9
	0	20,241.86	0	11,438	0
	10	20,747.91	2.5	11,701.07	2.3
	20	21,294.44	5.2	11,987.02	4.8

Table 14 shows that diesel prices mainly affect total operating cost, while their influence on carbon emissions is very limited. Weather-adjusted operational efficiency has the most significant influence on both objectives. When $\bar{W}_t$ decreases by 20%, total cost and carbon emissions increase by 11.19% and 7.28%, respectively; when $\bar{W}_t$ increases by 20%, they decrease by 18.02% and 18.57%, respectively. This indicates that selecting suitable operation windows is important for reducing cost and emissions.

The capacities of harvesters and grain trucks have moderate effects on the scheduling results. Lower harvester grain tank capacity V_h^{max} or lower grain truck capacity Q_c increases unloading frequency, transportation demand, and coordination pressure, thereby increasing cost and carbon emissions. Crop yield ρ_i also shows a positive relationship with both objectives, because higher yield increases grain transportation demand and unloading workload. Overall, the sensitivity analysis suggests that weather-adjusted operational efficiency, crop yield, and grain truck capacity are key factors that should be considered in practical harvesting organization.

5.5. Retrospective Case-Based Comparison

To verify the optimization effectiveness and practical value of the proposed method in real agricultural production scheduling, this section compares it with the current empirical scheduling strategy employed by the farm. During the harvesting period, experience-based scheduling typically relies on the dispatcher's empirical judgment. Its core principles can be summarized as "nearest service" and "sequential operation", where tasks are preferentially assigned to the nearest available machinery and executed in the

order of field indices or spatial locations. Such a strategy lacks global coordination and does not explicitly consider the joint optimization of total operating cost and carbon emissions at the system level.

In this study, the experience-based scheduling scheme was reconstructed by tracking and recording the actual harvesting operations conducted at Jianbian Farm during the corn harvesting period in September 2025 for the considered case area. The corresponding operating costs were calculated based on the recorded machinery usage and travel information, while carbon emissions were estimated using the same emission coefficients and calculation method adopted in the proposed model. It should be noted that the ALA-AN-based scheduling scheme was generated computationally and was not physically implemented on the farm. Therefore, this section is presented as a retrospective case-based comparison rather than an experimental verification. The retrospective case-based comparison adopts the same case scenario as in Section 4.2, including 27 corn fields to be harvested, one machinery depot, four combine harvesters, and five grain trucks, with all tasks completed within 10 days, using the same basic data shown in Tables 2 and 3. The ALA-AN-based scheduling plan directly adopts the average best results obtained from 10 independent runs reported in Table 10. By comparing the total operating cost and total carbon emissions under the two scheduling strategies, the practical benefits of the proposed optimization approach can be objectively evaluated. Table 15 reports on the total operating cost and total carbon emissions obtained by the experience-based strategy and the ALA-AN-based scheduling plan.

Table 15. Comparison results of different scheduling schemes.

Scheduling Method	Total Cost	Total Carbon Emissions	Improvement
Experience-based scheduling	21,500.00	11,800.00	-
ALA-AN-based scheduling	20,241.86	11,438.00	Cost −5.85%; carbon −3.07%

Based on the comparative results in Table 15, the ALA-AN-based scheduling scheme shows potential advantages over the experience-based strategy in both economic and environmental aspects under the same retrospective case conditions. Specifically, the estimated total operating cost is reduced by approximately 5.85%, mainly due to the global optimization of machinery routing, especially the routing of grain trucks. By reducing empty travel distance, waiting time, and unnecessary detours, the proposed approach shows the potential to improve machinery resource utilization and overcome the limitations of local, experience-driven decision making. Meanwhile, the estimated total carbon emissions are reduced by approximately 3.07%, which can be attributed to more rational route planning and operation sequencing that shorten the overall travel distance and reduce high-energy-consumption operating conditions. These results indicate that the proposed method has the potential to jointly reduce operating cost and carbon emissions in low-carbon agricultural scheduling scenarios. However, beyond the numerical comparison with benchmark algorithms, the practical implications of these results should be further interpreted in relation to field-work organization, harvest logistics, and agricultural greenhouse gas mitigation, as discussed in the following subsection.

5.6. Comparison with Previous Studies and Practical Implications

The obtained results can be further interpreted in the context of previous studies on field-work organization, harvest logistics, and low-carbon agricultural machinery management. Previous research on agricultural machinery scheduling has shown that reasonable field assignment, route planning, and machine coordination are essential for reducing non-productive travel, machinery waiting time, and operating cost [14–16,24,32]. The results of this study are consistent with these findings. In the optimized scheduling scheme,

the assignment of harvesters is not determined by simple workload balance but by the spatial distribution of fields and the system-level objective of minimizing total operating cost and carbon emissions. For example, although harvester h_4 undertakes a larger operating area, this arrangement reduces unnecessary cross-regional transfers and avoids additional fuel consumption caused by forced workload balancing. This indicates that in large-scale harvesting operations, balanced machine workload is not always equivalent to system-level efficiency. A spatially coordinated field-work organization can be more effective for reducing total travel distance, idle movement, and energy consumption.

From the perspective of harvest logistics, previous studies on harvester–grain truck coordination have mainly emphasized reducing harvester waiting time, truck transfer distance, and total operation duration [26,37]. The present study supports this research direction but further extends it by explicitly modeling the field–harvester–truck service relationship and grain tank synchronization. The case results show that the transport efficiency of grain trucks is closely related not only to travel distance but also to field spatial continuity, task density, and the matching relationship with harvesters. Grain trucks operating in compact field clusters tend to have shorter and more direct service routes, whereas trucks serving spatially dispersed fields are more likely to generate detours, return trips, and waiting time. This finding confirms that harvest logistics should be organized at the system level rather than according to isolated nearest-service or sequential-operation rules. The proposed framework therefore provides a more integrated decision-making tool for coordinating harvesting and grain transportation processes.

In terms of greenhouse gas emission reduction, existing studies have pointed out that inefficient machinery movement, excessive field transfer, and poor coordination among machines can increase fuel consumption and agricultural carbon emissions [5,11–13]. The results of this study provide quantitative support for this conclusion. In the retrospective case-based comparison, the ALA-AN-based scheduling scheme reduced the estimated total operating cost by 5.85% and the estimated total carbon emissions by 3.07% compared with the experience-based scheduling scheme. These reductions are mainly attributed to the coordinated optimization of field operation sequencing, harvester assignment, grain truck service matching, and route planning. Compared with studies that treat carbon emissions only as a post-evaluation indicator, the proposed model incorporates carbon emissions directly into the optimization objective. This allows the trade-off between economic performance and environmental impact to be considered during the scheduling process rather than after the schedule has been generated.

Furthermore, the proposed model extends previous agricultural machinery scheduling studies by incorporating weather-dependent operational efficiency into the cooperative scheduling framework. Although the current scenario-based weather representation is still a simplified approximation, it reflects the fact that harvesting efficiency may vary under different weather conditions and that unsuitable weather can interrupt field operations. This improves the practical relevance of the scheduling model compared with models that assume constant operating efficiency throughout the entire harvesting period.

Overall, the results are consistent with previous findings that optimized machinery scheduling can improve field-work organization and harvest logistics efficiency. More importantly, this study demonstrates that these operational improvements can also contribute to greenhouse gas emission reduction when carbon emissions are considered as a direct optimization objective. Therefore, the proposed framework complements previous research by linking field operation organization, harvester–grain truck logistics, and low-carbon agricultural machinery scheduling within a unified multi-objective optimization model.

6. Conclusions

This study developed a multi objective collaborative scheduling model for harvesters and grain trucks to simultaneously minimize total operational cost and carbon emissions under realistic agricultural operating conditions. The proposed model integrates field operation sequencing, machine capacity limitations, routing decisions, weather-dependent operational efficiency, and harvester–truck synchronization requirements, enabling a comprehensive representation of harvesting and grain transportation activities in large-scale farming systems.

To solve the resulting complex optimization problem, an improved artificial lemming algorithm with adaptive behavior selection and neighborhood cooperation (ALA-AN) was proposed. The algorithm incorporates a three-layer encoding structure, an enhanced population initialization strategy, an adaptive search mechanism, and a neighborhood-cooperative update strategy to improve solution quality and search efficiency. These improvements enable the algorithm to effectively address the strong coupling and multi-objective characteristics of agricultural machinery scheduling problems.

Experimental results based on real farm data and multiple scheduling scenarios demonstrated that the proposed approach consistently achieved lower operational costs and carbon emissions than the benchmark algorithms. In the case study of Jianbian Farm, the optimized schedule reduced the estimated total operating cost by 5.85% and carbon emissions by 3.07% compared with the empirical scheduling strategy. Statistical analyses further confirmed the robustness and effectiveness of the proposed approach, particularly in medium- and large-scale scheduling scenarios. The results indicate that coordinated scheduling of harvesters and grain trucks can significantly improve machinery utilization, reduce unnecessary transportation activities, decrease harvester waiting time, and support low-carbon agricultural operations. The sensitivity analysis further indicates that weather-adjusted operational efficiency, crop yield, and grain truck capacity are the main factors affecting total cost and carbon emissions, suggesting that weather conditions, yield distribution, and transport capacity should be fully considered when preparing practical harvesting schedules. Therefore, the proposed framework can serve as an effective decision-support tool for intelligent agricultural machinery management and sustainable harvesting operations.

Several limitations should be acknowledged. The proposed model considers the cooperative scheduling of harvesters and grain trucks but assumes homogeneous technical parameters within each machinery type. Machine breakdowns, refueling interruptions, maintenance needs, operator performance differences, terrain-dependent fuel consumption, soil moisture, road conditions, and field trafficability are not explicitly considered. In addition, weather scenario probabilities and efficiency coefficients are treated as exogenous inputs rather than dynamically updated using real-time forecasts. Future research will incorporate machine-specific parameters, stochastic operational disturbances, terrain- and soil-condition-adjusted fuel consumption models, real-time weather and machine-position data, and dynamic rescheduling mechanisms. Field implementation or semi-physical simulation experiments will also be conducted to validate the practical applicability of the proposed method.

Author Contributions: Conceptualization, J.-L.B. and J.-Q.W.; methodology, J.-L.B. and J.-Q.W. software, J.-L.B. and J.-Q.W.; validation, J.-L.B. and J.-Q.W.; formal analysis, J.-L.B. and J.-Q.W. investigation, J.-L.B. and J.-Q.W.; resources, J.-L.B. and J.-Q.W.; data curation, J.-L.B. and J.-Q.W. writing—original draft preparation, J.-L.B.; writing—review and editing, J.-Q.W.; visualization, J.-L.B. and J.-Q.W.; supervision, J.-Q.W.; project administration, J.-L.B. and J.-Q.W.; funding acquisition, J.-Q.W. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Found of China, grant number 21BGL174.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Acknowledgments: The authors thank the anonymous reviewers for their valuable and constructive comments that greatly helped improve the quality and completeness of this paper.

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

Nomenclature

Notations Descriptions

F	Fields set $F = \{0, 1, 2, \dots, n\}$, where 0 represents the machine depot
H	Harvester set $H = \{1, 2, \dots, m\}$
C	Grain trucks set $C = \{1, 2, \dots, l\}$
(x_i, y_i)	The coordinates of field i , where $i \in \{0, 1, 2, \dots, n\}$
A_i	The area of field i (hm ²)
A_{ih}^R	When the harvester h is in an empty warehouse state, the area in field i that has not been harvested yet
ρ_i	The yield per unit area of field i
γ	Grain density
E_h	Operating efficiency of harvester h
v_h	Operating speed of harvester h
V_i^h	The grain load of harvester h when operating on field i
$V_h^{\max}$	Maximum grain storage capacity of harvester h
Q_c	Capacity of grain trucks c
v_c	Travel speed of grain truck c
N_c	Total number of trips for grain truck c
f_h^{travel}	Fuel consumption rate of harvester h during travel
f_h^{work}	Fuel consumption rate of harvester h during field operation
f_c^{travel}	Fuel consumption rate of grain truck c during travel
P_f	Diesel price
c^{penalty}	The penalty cost for harvester waiting for a grain truck
d_{ij}	The distance between field i and field j (km) $i, j \in \{0, 1, 2, \dots, n\}$
t_i^h	Start time of harvester h at field i when its grain tank enters the empty state
t_{ic}^h	The time when grain truck c is fully loaded by harvester h while operating on field i
t_c^{unload}	The unloading time required by grain truck c
t_w^h	Maximum allowable waiting time for harvester h
tot_i^h	The total operating time of harvester h on field i
CEH	Carbon emissions per unit distance traveled by the harvester
CEA	Carbon emissions per unit area operated by a harvester
CEC	Carbon emissions per unit distance traveled by grain truck
x_{ij}^h	If harvester h travels from field i to field j , the value is 1; otherwise, it is 0
x_i^h	If harvester h is operating on field i , the value is 1; otherwise, it is 0
y_{ij}^c	If the grain truck c travels from the field i to field j , the value is 1; otherwise, it is 0
D	The number of harvesting days required by the farm
u_i^h	The visiting order of field i in the route of harvester h
S_{ihc}	$S_{ihc} = 1$ if grain truck c provides transportation service for harvester h operating in field i ; otherwise, $S_{ihc} = 0$
L_{ic}	The load of grain truck c after serving field i
B_i^h	The grain tank load of harvester h after operating in field i
Ω	Set of weather scenarios
ω	Weather scenario, $\omega \in \Omega$
p_ω	Probability of weather scenario ω
W_t^ω	Weather-dependent operational efficiency coefficient in time period t under weather scenario ω

$$\bar{W}_t \quad \text{Expected weather-adjusted operational efficiency coefficient in time period } t, \\ \bar{W}_t = \sum_{\omega \in \Omega} p_{\omega} W_t^{\omega}$$

References

1. Karagiannis, P.; Kotsaris, P.; Xanthakis, V.; Vasilaros, P.; Michalos, G.; Makris, S.; van Evert, F.K.; Nieuwenhuizen, A.T.; Fountas, S.; Chrysosolouris, G. On an intelligent system to plan agricultural operations. *Smart Agric. Technol.* **2025**, *10*, 100707.
2. Li, S.; Zhang, M.; Wang, N.; Cao, R.; Zhang, Z.; Ji, Y.; Li, H.; Wang, H. Intelligent scheduling method for multi-machine cooperative operation based on NSGA-III and improved ant colony algorithm. *Comput. Electron. Agric.* **2023**, *204*, 107532.
3. Liu, Q.; Yu, R.; Suo, H.; Cai, Y.; Chen, L.; Jiang, H. Autonomous Driving in Agricultural Machinery: Advancing the Frontier of Precision Agriculture. *Actuators* **2025**, *14*, 464.
4. Zhuang, M.; Wang, X.; Yang, Y.; Wu, Y.; Wang, L.; Lu, X. Agricultural machinery could contribute 20% of total carbon and air pollutant emissions by 2050 and compromise carbon neutrality targets in China. *Nat. Food* **2025**, *6*, 513–522.
5. Wu, B.; Wu, Z.; Yao, Z.; Li, J.; Wang, W.; Shen, X.; Hao, X. Multi-type emission factors quantification of black carbon from agricultural machinery based on the whole tillage processes in China. *Environ. Pollut.* **2022**, *314*, 120280.
6. Mattetti, M.; Annesi, G.; Intrevado, F.P.; Alberti, L. Investigating the efficiency of hybrid architectures for agricultural tractors using real-world farming data. *Appl. Energy* **2025**, *377*, 124499.
7. Yang, Q.; Wei, M.; Su, J.; Duan, Y.; Zhu, J. Multi-objective optimization of hybrid agricultural powertrain via crowding-adaptive NSGA-II with dynamic population control. *Energy* **2025**, *335*, 138124.
8. Ma, H.; Ning, J.; Zheng, J.; Zhang, C. A Decomposition-Based Evolutionary Algorithm with Neighborhood Region Domination. *Biomimetics* **2025**, *10*, 19.
9. He, P.; Li, J.; Zhang, D.; Wan, S. Optimisation of the harvesting time of rice in moist and non-moist dispersed fields. *Biosyst. Eng.* **2018**, *170*, 12–23.
10. Cerdeira-Pena, A.; Carpenete, L.; Amiana, C. Optimised forage harvester routes as solutions to a traveling salesman problem with clusters and time windows. *Biosyst. Eng.* **2017**, *164*, 110–123.
11. Liu, H.; Zhang, L.; Zhao, B.; Tang, J.; Luo, J.; Wang, S. Research on emergency scheduling based on improved genetic algorithm in harvester failure scenarios. *Front. Plant Sci.* **2024**, *15*, 1413595.
12. Luo, X.W.; Zhang, L.Y. The Optimal Scheduling Model for Agricultural Machinery Resources with Time-Window Constraints. *Int. J. Simul. Model.* **2016**, *15*, 721–731.
13. Quintero, H.F. Metaheuristic Optimization of Agricultural Machinery for the Colombian Carnation Industry. *Agronomy* **2024**, *14*, 2589.
14. Liu, X.; Shao, P.; Li, G.; Ye, L.; Yang, H. Complex hilly terrain agricultural UAV trajectory planning driven by Grey Wolf Optimizer with interference model. *Appl. Soft Comput.* **2024**, *160*, 111710.
15. Wu, Y.; Fang, H. Agricultural machinery scheduling under time window constraints using deep reinforcement learning. *Biosyst. Eng.* **2025**, *257*, 104188.
16. Jarumaneeroj, P.; Oak Dusadeerungsikul, P.; Chotivanich, T.; Akkerman, R. A multi-objective modeling approach to harvesting resource scheduling: Decision support for a more sustainable Thai sugar industry. *Comput. Ind. Eng.* **2021**, *162*, 107694.
17. Wang, N.; Li, S.; Xiao, J.; Wang, T.; Han, Y.; Wang, H.; Zhang, M.; Li, H. A collaborative scheduling and planning method for multiple machines in harvesting and transportation operations-Part I: Harvester task allocation and sequence optimization. *Comput. Electron. Agric.* **2025**, *232*, 110060.
18. Wang, N.; Li, S.; Xiao, J.; Wang, T.; Han, Y.; Wang, H.; Zhang, M.; Li, H. A collaborative scheduling and planning method for multiple machines in harvesting and transportation operations-part II: Scheduling and planning of harvesters and grain trucks. *Comput. Electron. Agric.* **2025**, *235*, 110344.
19. Aijaz, N.; Lan, H.; Raza, T.; Yaqub, M.; Iqbal, R.; Pathan, M.S. Artificial intelligence in agriculture: Advancing crop productivity and sustainability. *J. Agric. Food Res.* **2025**, *20*, 101762.
20. Kivekäs, K.; Lajunen, A. Energy efficiency and carbon dioxide emissions of agricultural tractors using different powertrains. *Energy Rep.* **2025**, *14*, 2755–2767.
21. Cong, C.; Jianping, H.; Qingkai, Z.; Meng, Z.; Yibai, L.; Feng, N.; Guangqiao, C. Research on the Scheduling of Tractors in the Major Epidemic to Ensure Spring Ploughing. *Math. Probl. Eng.* **2021**, *2021*, 3534210.
22. Ma, L.; Xin, M.; Wang, Y.-J.; Zhang, Y. Dynamic Scheduling Strategy for Shared Agricultural Machinery for On-Demand Farming Services. *Mathematics* **2022**, *10*, 3933.

23. Huang, H.; Cuan, X.; Chen, Z.; Zhang, L.; Chen, H. A Multiregional Agricultural Machinery Scheduling Method Based on Hybrid Particle Swarm Optimization Algorithm. *Agriculture* **2023**, *13*, 1042.
24. Zhang, C.; Jia, L.; Liu, S.; Dou, G.; Liu, Y.; Kong, B. Dynamic job allocation method of multiple agricultural machinery cooperation based on improved ant colony algorithm. *Sci. Rep.* **2024**, *14*, 22414.
25. Pan, W.; Wang, J.; Yang, W. A Cooperative Scheduling Based on Deep Reinforcement Learning for Multi-Agricultural Machines in Emergencies. *Agriculture* **2024**, *14*, 772.
26. Liu, H.; Luo, J.; Yu, H.; Tang, J.; Wang, F.; Wang, S. Intelligent cooperative scheduling and path planning for tracked maize harvesters and grain trucks using an enhanced hybrid MOEA/D-LSA algorithm. *Comput. Electron. Agric.* **2025**, *239*, 110952.
27. Jiang, Y.; Li, X.; Yang, Z.; Zhang, X.; Wu, H. An adaptive immune-following algorithm for intelligent optimal schedule of multi-regional agricultural machinery. *Int. J. Intell. Syst.* **2022**, *37*, 9404–9423.
28. He, P.; Li, J.; Wang, X. Wheat harvest schedule model for agricultural machinery cooperatives considering fragmental farmlands. *Comput. Electron. Agric.* **2018**, *145*, 226–234.
29. Cao, R.; Li, S.; Ji, Y.; Zhang, Z.; Xu, H.; Zhang, M.; Li, M.; Li, H. Task assignment of multiple agricultural machinery cooperation based on improved ant colony algorithm. *Comput. Electron. Agric.* **2021**, *182*, 105993.
30. Xing, T.; Dehghanian, P.; Yang, D. Optimal scheduling strategies for agricultural park integrated energy systems: An extensive review and prospects. *Renew. Sustain. Energy Rev.* **2025**, *221*, 115931.
31. Guo, D.; Olesen, J.E.; Manevski, K.; Ma, X. Optimizing irrigation schedule in a large agricultural region under different hydrologic scenarios. *Agric. Water Manag.* **2021**, *245*, 106575.
32. Liu, X.; Zhu, X.; Hao, K. Dynamic immune cooperative scheduling of agricultural machineries. *Complex Intell. Syst.* **2021**, *7*, 2871–2884.
33. Guo, Y.; Zhang, F.; Chang, S.; Li, Z.; Li, Z. Research on a multiobjective cooperative operation scheduling method for agricultural machinery across regions with time windows. *Comput. Electron. Agric.* **2024**, *224*, 109121.
34. Jia, L.; Zhang, Q.; Liu, S.; Kong, B.; Liu, Y. Multi-Station Agricultural Machinery Scheduling Based on Spatiotemporal Clustering and Learnable Multi-Objective Evolutionary Algorithm. *AgriEngineering* **2025**, *7*, 197.
35. Miao, Z.; Guo, H.; Pan, Q.-k.; Peng, C.; Xu, Z. A reinforcement learning-enhanced multi-objective iterated greedy algorithm for weeding-robot operation scheduling problems. *Expert Syst. Appl.* **2025**, *263*, 125760.
36. Liu, H.; Luo, J.; Zhang, L.; Yu, H.; Zou, S.; Wang, S. Cooperative scheduling method for harvester and grain transport vehicle based on IMPA algorithm. *Int. J. Agric. Biol. Eng.* **2026**, *19*. <https://doi.org/10.25165/j.ijabe.20261901.9373>.
37. Morales Chavez, M.M.; Sarache, W.; Costa, Y.; Soto, J. Multiobjective stochastic scheduling of upstream operations in a sustainable sugarcane supply chain. *J. Clean. Prod.* **2020**, *276*, 123305.
38. Novoa-Flores, G.I.; Carpenente, L.; Lorenzo-Freire, S. Optimizing the production schedule of an agricultural cooperative: A case study. *Eng. Optim.* **2019**, *52*, 252–270.
39. Pillac, V.; Gendreau, M.; Guéret, C.; Medaglia, A.L. A review of dynamic vehicle routing problems. *Eur. J. Oper. Res.* **2013**, *225*, 1–11.
40. Carr, R.; Ravi, R.; Simonetti, N. A new integer programming formulation of the graphical traveling salesman problem. *Math. Program.* **2023**, *197*, 877–902.
41. Wang, Y.; Li, Q.; Guan, X.; Fan, J.; Xu, M.; Wang, H. Collaborative multi-depot pickup and delivery vehicle routing problem with split loads and time windows. *Knowl.-Based Syst.* **2021**, *231*, 107412.
42. Xiao, Y.; Cui, H.; Khurma, R.A.; Castillo, P.A. Artificial lemming algorithm: A novel bionic meta-heuristic technique for solving real-world engineering optimization problems: Artificial lemming algorithm...: Y. Xiao et al. *Artif. Intell. Rev.* **2025**, *58*, 1.
43. Mirjalili, S.; Rawlins, T.; Hettenhausen, J.; Lewis, A. A comparison of multi-objective optimisation metaheuristics on the 2D airfoil design problem. *ANZIAM J.* **2013**, *54*, 345–360.
44. Deb, K.; Pratap, A.; Agarwal, S.; Meyarivan, T. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* **2002**, *6*, 182–197.
45. Zhang, H.; Zhang, Q.; Ma, L.; Zhang, Z.; Liu, Y. A hybrid ant colony optimization algorithm for a multi-objective vehicle routing problem with flexible time windows. *Inf. Sci.* **2019**, *490*, 166–190.
46. Zhang, Y.; Li, H.; Wang, Z.; Wang, H. A Multi-Objective Learning Whale Optimization Algorithm for Open Vehicle Routing Problem with Two-Dimensional Loading Constraints. *Mathematics* **2024**, *12*, 2227–7390.
47. Kuo, R.; Luthfiansyah, M.; Masruroh, N.; Zulvia, F.E. Application of improved multi-objective particle swarm optimization algorithm to solve disruption for the two-stage vehicle routing problem with time windows. *Expert Syst. Appl.* **2023**, *225*, 120009.

48. Fang, Z.; Wang, X.; Sun, Y.; Adibhashimi, M.A. Accelerating multi-objective optimization of concrete thin shell structures using graph-constrained GANs and NSGA-II. *Sci. Rep.* **2025**, *15*, 16090.
49. Zaki, T.; Zeiträg, Y.; Neves, R.; Figueira, J.R. A cooperative coevolutionary genetic programming hyper-heuristic for multi-objective makespan and cost optimization in cloud workflow scheduling. *Comput. Oper. Res.* **2024**, *172*, 106805.
50. Friedman, M. The Use of Ranks to Avoid the Assumption of Normality Implicit in the Analysis of Variance. *J. Am. Stat. Assoc.* **1937**, *32*, 675–701.
51. Song, H.; Wang, J.; Song, L.; Zhang, H.; Bei, J.; Ni, J.; Ye, B. Improvement and application of hybrid real-coded genetic algorithm. *Appl. Intell.* **2022**, *52*, 17410–17448.

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