# Optimal scheduling of agricultural machines in hilly mountainous areas based on NSGA-Ⅱ-SA hybrid algorithm with applications

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**Abstract:** Optimizing the scheduling of farm machinery is essential to meet farmers' requirements, minimize scheduling costs, and save time. This study focuses on scheduling farm machinery in multiple cooperatives across various regions, aiming to minimize scheduling costs and reduce scheduling time. Initially, a multi-constraint hybrid clustering algorithm is employed to assign farmland to each farm machinery cooperative by clustering before scheduling. Subsequently, an enhanced version of the Non-dominated Sorting Genetic Algorithm-Ⅱ (NSGA-Ⅱ) is proposed, integrating a local search strategy based on congestion-based neighborhood search and the Simulated Annealing (SA) algorithm to develop the NSGA-Ⅱ-SA algorithm. This hybrid multi-objective evolutionary algorithm effectively optimizes scheduling costs and time. The model's validity and the algorithm's superiority are demonstrated through a Web-based multi-region agricultural machine scheduling system and an example study. Experimental results show that the NSGA-Ⅱ-SA algorithm significantly reduces scheduling costs and time, as well as the number of scheduled farm machines, outperforming other algorithms with reductions of 9.8%, 3.1%, and 8.7% in total scheduling costs, and 12.5%, 13.4%, and 11.6% in total scheduling time. This research establishes a theoretical framework for multi-region agricultural machine scheduling in hilly and mountainous areas, enhancing agricultural production efficiency.
**Keywords:** multi-region agricultural machine scheduling, hilly mountainous area, hybrid optimization algorithm, agricultural machine scheduling system
**DOI:** 10.25165/j.ijabe.20251805.9106

**Citation:** Liu H Y, Luo J H, Zhang L H, Wang F L, Wang S. Optimal scheduling of agricultural machines in hilly mountainous areas based on NSGA-Ⅱ-SA hybrid algorithm with applications. Int J Agric & Biol Eng, 2025; 18(5): 234–245.

## 1 Introduction

In the hilly mountainous areas of Sichuan, farmland is widely distributed and scattered, with relatively small areas that make farmers heavily reliant on agricultural machinery cooperatives for resource support during production[1]. The complex geographical, multifactorial, and dynamic nature of multi-region farm machinery scheduling in these areas often poses challenges for traditional scheduling schemes to operate optimally due to the unique geography, thus hindering the development of agricultural mechanization[2-5]. Addressing the need to efficiently complete all farmland tasks simultaneously while minimizing scheduling time and costs has become a pressing issue in agricultural machinery scheduling in hilly mountainous regions[6-8]. This paper aims to delve into the multi-region agricultural machinery scheduling problem in these areas by developing mathematical models and utilizing advanced algorithms to optimize routes and timing for each agricultural machine, ultimately maximizing resource utilization.

With the advancement of research, various studies have delved into the dynamic multi-region scheduling problem of agricultural machinery. Some works have focused on non-dominated neighborhood selection and taboo search immunity algorithms[9], while others have explored the challenges of multi-region emergency scheduling, taking into account factors such as scheduling cost and time due to the time-sensitive nature of agricultural operations[10-12]. Additionally, there have been investigations into emergency scheduling models and algorithms for multi-region farm machinery operations, aiming to minimize scheduling costs and losses[13]. Furthermore, approaches like the improved multi-parent genetic algorithm for farm machinery inter-region operation planning have been proposed to optimize scheduling times[14]. Other studies have looked into scheduling algorithms for farm machinery across multiple farmlands, considering external factors like weather to enhance machinery utilization[15-21]. Harvest scheduling problems for multiple farmland operating sites have also been examined, with a focus on minimizing total operating time and considering time windows to reduce costs[22-24] Moreover, the complexity of multi-farm operations with factors like multiple banks, models, and time windows has been explored[25]. Some research has even analyzed multi-farm, multi-cycle problems to boost crop yield[26].

Existing studies have shown a lack of research on multiregional farm machinery scheduling in hilly mountainous areas, particularly in relation to operational timeliness. This poses a significant challenge in optimizing scheduling costs and time due to the complex and uncertain nature of managing different farmlands in such regions. As a result, there is a knowledge gap on how to efficiently schedule farm machinery across multiple regions while taking into account factors such as scheduling distance, time window, farm machinery capacity, and machinery capability[27]. The basic hypothesis of this study is to develop an efficient multi-

**Received date:** 2024-05-29 **Accepted date:** 2025-05-26
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objective optimization model by using a hybrid clustering algorithm with multiple constraints and combining neighborhood search and local search strategies, so as to effectively solve the complex problem of scheduling agricultural machines in hilly mountainous areas. Specifically, the NSGA-Ⅱ-SA algorithm solution model is proposed to handle the multi-region agricultural machine scheduling problem, aiming to minimize costs and time while adhering to operational constraints. To demonstrate the effectiveness and practicality of the proposed method, a Web-based multi-region agricultural machine scheduling system will be developed, and an illustrative case study will be conducted. This research aims to provide a theoretical foundation and practical tool for addressing the challenges of high costs and poor timeliness associated with multi-region agricultural machine scheduling in hilly mountainous areas, ultimately contributing to the improvement of agricultural operations in these challenging environments.

This paper outlines the research as follows: Section Ⅰ provides the background of related research and acknowledges the contributions of other scholars. Section Ⅱ introduces the mathematical model and the hybrid algorithmic process involving improved NSGA-Ⅱ and simulated annealing. Section Ⅲ analyzes and validates an example using farmland in the experimental area, discussing and verifying the effectiveness and superiority of the algorithm. Section Ⅳ details the design of an agricultural machine scheduling system to offer software support for multi-region agricultural machine scheduling. A discussion of this study is presented in Section Ⅴ. Finally, Section Ⅵ concludes the paper.

## 2 Scheduling model

### 2.1 Description of the problem

This study addresses the multiregional farm machinery scheduling problem, where $M$ farm cooperatives schedule farm machinery to $N$ farmlands for operation. Each farm machinery cooperative possesses a specific number of farm machinery. Prior to conducting the study, the following issues must be taken into consideration.

In the process of multi-region scheduling, it is essential to consider the interconnected factors of time, space, and resources, which pose a significant challenge to problem-solving. To develop a rational scheduling plan for farm machinery, the following supply and demand process must be followed: farmers communicate their needs to farm machinery cooperatives, and the cooperatives schedule machinery based on the operational demand, including details such as farmland size, quantity, and location (see Figure 1).

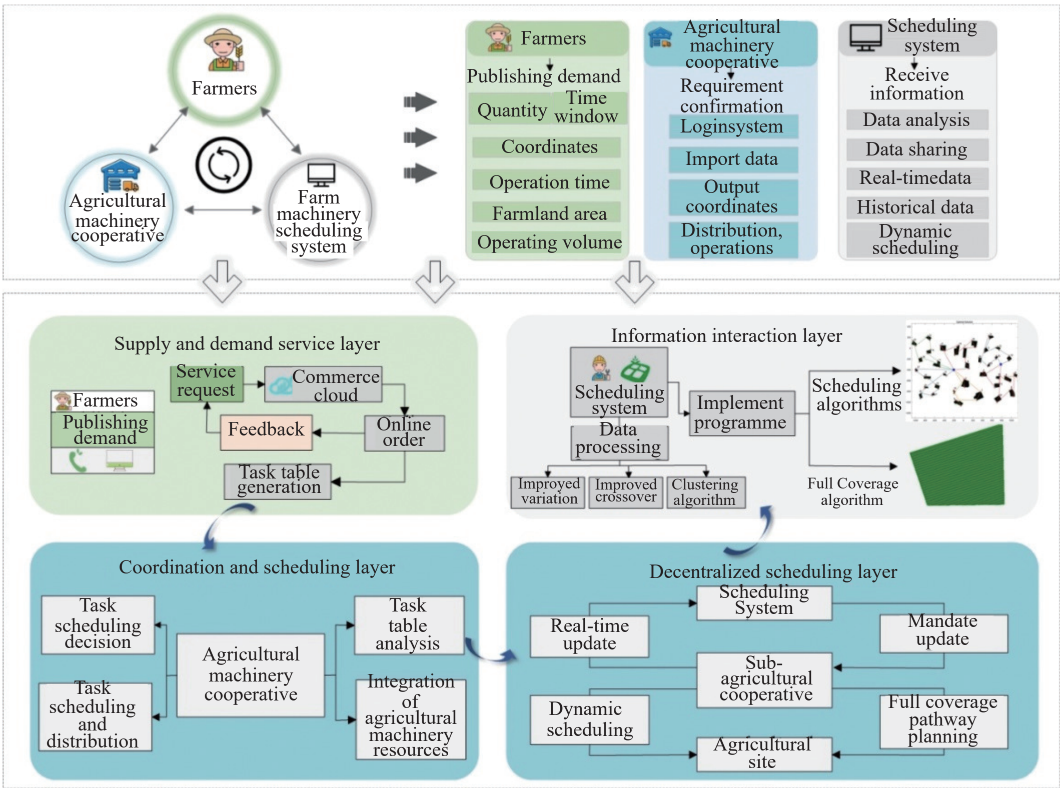



Figure 1 Schematic of supply and demand decisions

### 2.2 Scheduling goal

This paper addresses the multi-region agricultural machinery scheduling problem by taking into account different factors that impact the operation of agricultural machinery. A mathematical model is developed, which comprehensively incorporates scheduling objectives in various aspects.

(1) Minimize scheduling cost

Given the inherent difficulty in altering the area of farmland and the distance between fields, reducing scheduling costs becomes imperative for enhancing revenue. The scheduling costs analyzed in this study encompass four key components: the start-up cost of farm machines, which represents the fixed cost incurred each time a machine is activated; the cost of operating farm machines, calculated based on the total distance covered in the field; the cumulative costs associated with in-field operation paths; and the cost of waiting and penalties. The latter factor considers soft time-window constraints, where machines may arrive at the operation point either ahead of or after the designated time window, resulting in additional costs for waiting and penalties.

The analysis of scheduling costs reveals that utilizing fewer farm machines can lower start-up costs, while reducing the total distance of scheduling can effectively decrease overall costs and enhance resource utilization of farm machines.

(2) Minimize scheduling time

The scheduling time discussed in this study comprises three components: waiting time, transfer time, and operation time. Waiting time is the period between the arrival of the farm machine at the operation point and the beginning of the time window. Transfer time is the time taken for the farm machine to move between operation points. Operation time is the duration required to complete the full coverage path of the farm operation point.

## 2.3 Definitions and assumptions

This study focuses on optimizing schedule costs and time efficiency in a hilly mountainous region with multiple farmlands and farm cooperatives. The goal is to ensure all farm tasks are completed while minimizing costs and time. The problem assumptions were established prior to the study.

(1) Each farm machine departs from its respective farm machinery cooperative and returns to the same cooperative;

(2) The number of farm machines used must not exceed the total number available;

(3) Each farmland can only be worked by one farm machine;

(4) Each farm machine that arrives at the farmland must adhere to time window constraints. This paper employs soft time window constraints, resulting in waiting time and costs incurred before the workable time, as well as penalty costs incurred after the workable time;

(5) Each operating route should not exceed the maximum distance traveled by the farm machine;

(6) Each farmland should not exceed the operating capacity of the farm machine;

(7) It is assumed that there are no obstacles or potential farm machinery failure phenomena in the process of scheduling farm machinery.

## 2.4 Mathematical models

### 2.4.1 Description of variables and parameters

First, define the set of farm machines as $m = \{M_1, M_2, ..., M_k\}$; the set of farm cooperatives as $a = \{A_1, A_2, ..., A_k\}$; the set of farmland as $f = \{F_1, F_2, ..., F_k\}$; and the set of capacity of farm machines as $q = \{q_1, q_2, ..., q_k\}$, where $k$ represents the maximum value. Taking into account various influencing factors in the model conditions, a mathematical model for multi-region farm machine scheduling with soft time windows and capacity constraints is established. The objectives of this model are to minimize scheduling costs and time. Additional parameters are defined as outlined in Table 1.

### 2.4.2 Scheduling objectives

The minimum integrated scheduling cost $C$ is utilized as the primary objective function, represented by Equation (1). This cost includes the total start-up cost, traveling cost, operating cost, and penalty time cost. The shortest scheduling time $T$ is employed as the secondary objective function, depicted in Equation (2). This time encompasses waiting time, transfer time, and operating time.

$$\min C = \sum_{m=1}^{M} C_{0m} + C_1 \sum_{i=1}^{F+A}\sum_{j=1}^{F+A}\sum_{m=1}^{M} x_{ijm} d_{ij} + C_5 \sum_{i=1}^{F}\sum_{m=1}^{M} X_i^m S_i + \sum_{m=1}^{M} P_m \tag{1}$$

$$\min T = \sum_{i=1}^{M} w_{mi} + C_2 \sum_{i=1}^{F+A}\sum_{j=1}^{F+A} t_{ij} + \sum_{i=1}^{F} T_i \tag{2}$$

The constraints are as follows:

**Table 1 Variable parameter definitions**

| Parameter | Description |
|---|---|
| $C_{0m}$ | Start-up cost of farm machinery |
| $C_1, C_2, C_3, C_4, C_5$ | Cost per unit distance traveled, cost per unit time transferred, cost per unit time waited, cost per unit time penalized, cost per unit area worked on |
| V | Traveling speed of farm machinery |
| $T_i$ | Operating time of the farmland *i* in seconds |
| $S_i$ | Cost of operation for farm field *i* (CNY) |
| $P_m$ | Time cost of operation of farm machine m (CNY) |
| $q_i$ | Demand for operations on farmland *i* |
| $D_m$ | Maximum distance traveled by farm machine *m* |
| $t_{mi}$ | Time node when farm machine m arrives at farm field *i* |
| $T_i^M$ | Completion time of operation of farm machine m in farmland *i* |
| $d_{ij}$ | Distance from farmland *i* to farmland *j* |
| $X_{ijm}$ | Decision variables of farm machine m from farmland *i* to farmland *j* |
| $X_i^m$ | Farm machine m operates over farmland *i* |
| $b_i, e_i$ | the start time of the operation allowed in farmland *i*, the latest completion time of the operation allowed in farmland *i* |
| $w_{mi}$ | Waiting time for farm machine m to reach farmland *i* earlier than the operation time |

$$\sum_{i=1}^{A}\sum_{j=1}^{F}\sum_{m=1}^{M} x_{ijm} = M \tag{3}$$

$$\sum_{j=1}^{F}\sum_{m=1}^{M} x_{ijm} = 1;\ \ (i \in f) \tag{4}$$

$$\sum_{i=1}^{F+A}\sum_{j=1}^{F+A} x_{ijm} d_{ij} \le D_m;\ \ m \in \{1,2,\dots M\} \tag{5}$$

$$\sum_{i=1}^{M} Q_i \ge \sum_{i=1}^{F} q_i \tag{6}$$

$$w_{mi} = \max(0, b_i - t_{mi});\ \ (i \in f, m \in \{1,2,\dots M\}) \tag{7}$$

$$t_{mi} = t_{mj} + w_{mj} + T_j + t_{ij} \tag{8}$$

$$t_{ij} = \frac{d_{ij}}{V};\ \ (i, j \in f \cup m) \tag{9}$$

$$\sum_{i=1}^{F+A}\sum_{j=1}^{F+A} x_{ijm} q_i \le Q_m;\ \ m \in \{1,2,\dots M\} \tag{10}$$

$$P_m = \begin{cases} C_3(b_i - t_{mi}); \\ C_4(t_{mi} - e_i);\ \ (i \in f) \\ 0,\ \text{others}; \end{cases} \tag{11}$$

$$X_{ijm} = \begin{cases} 1, & \text{Agricultural machine } m \text{ travelling from farmland } i \text{ to farmland } j \\ 0, & \text{Agricultural machine } m \text{ not travelling from farmland } i \\ & \text{to farmland } j \end{cases} \tag{12}$$

Equation (3) indicates that all farm machinery departs from the farm cooperatives and eventually returns to their respective farm cooperatives. Equation (4) ensures that each farm machine will only work on each field once. Equation (5) restricts each farm machine from traveling more than its maximum allowed distance. Equation (6) guarantees that the operating capacity of all farm machinery is greater than or equal to the demand at the farm site. Equation (7) accounts for the waiting time between farm machinery operations. Equation (8) defines the time to reach farmland $i$ as the sum of the time to reach the previous farmland, the waiting time, the operating time of the previous farmland, and the operating time from the previous farmland to the current farmland. Equation (9) represents the transfer time between different farmland locations. Equation (10) constrains the total farmland capacity serviced on each route to not exceed the maximum loading capacity of the farm machinery. Equation (11) incorporates the time window constraint: when a farm machine operates on a farmland, it can only operate within a specific time window $[b_i, e_i]$ to maximize operational effectiveness. If the machine arrives before the start of the time window, it will incur a waiting time and cost; if it arrives after the start, it will incur a penalized time cost. Equation (12) defines the decision variables, using a binary (0–1) variable to indicate whether or not farm machine $m$ traveled from farm field $i$ to farm field $j$.

### 2.5 Algorithmic improvements

The multiregional agricultural machine scheduling problem is an NP-Hard problem with multiple constraints in a complex environment. The improved second-generation non-dominated sorting genetic algorithm (NSGA-Ⅱ) is considered one of the best multi-objective genetic algorithms for solving NP-Hard problems[28]. NSGA-Ⅱ maintains solution diversity through non-dominated sorting and congestion distance, leading to good convergence. However, NSGA-Ⅱ prioritizes solution quality over local search ability, which can result in falling into local optima and inefficient search during optimization. To overcome these limitations, this study proposes a hybrid multi-objective evolutionary algorithm called NSGA-Ⅱ-SA. This algorithm integrates clustering and scheduling concepts to address the multi-objective optimization problem of scheduling agricultural machines in hilly and mountainous areas. By enhancing NSGA-Ⅱ with neighborhood search based on crowding degree and simulated annealing, the algorithm gains improved flexibility and fine-tuning capabilities within the solution space. This enhancement also enhances the algorithm's ability to escape local optimal solutions. The algorithm flow is depicted in Figure 2.

The specific steps of the algorithm are as follows:

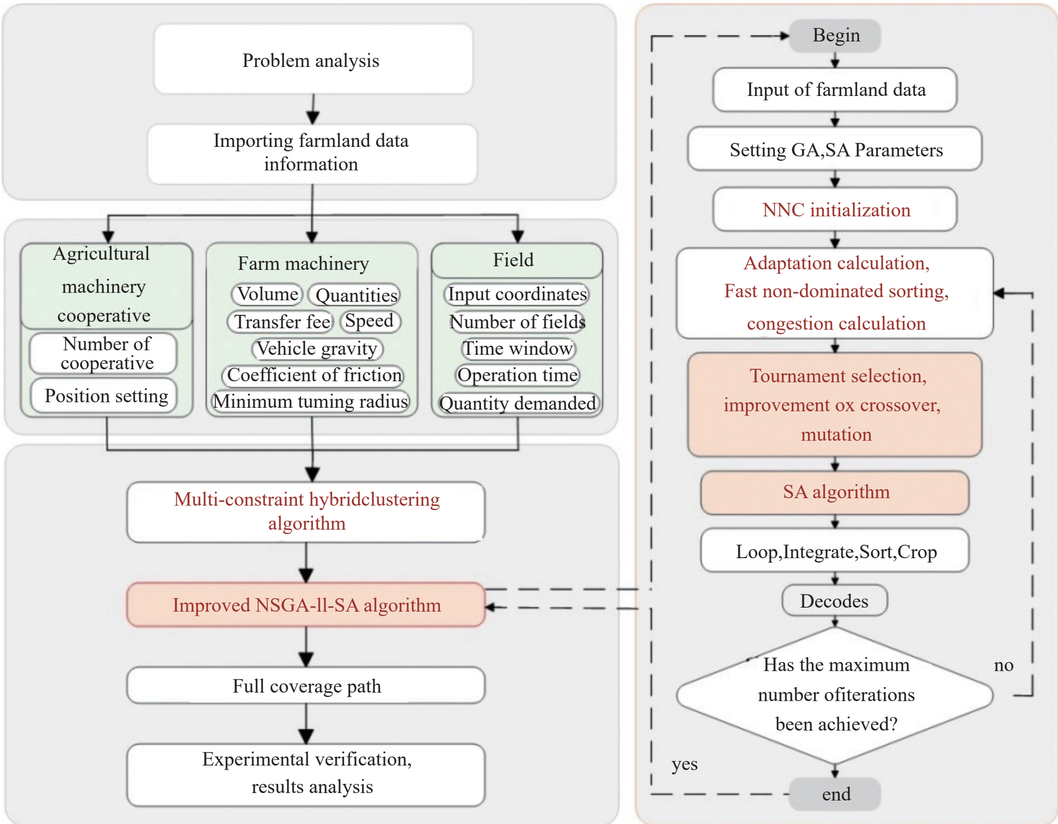



Figure 2 Overall algorithm framework

(1) Algorithm parameter setting. Algorithm parameter setting includes defining population size, number of iterations, probability of crossover variation, initial temperature, cooling factor, maximum number of iterations for outer and inner loops, and probabilities of exchange, reversal, and insertion.

(2) Coding and decoding. In this study, a two-segment coding approach is utilized, with the chromosome represented as an integer sequence. The genes in the first half of the chromosome correspond to agricultural machines and farmland numbers, while the genes in the second half indicate the order of farmland operation by the respective agricultural machines. Figure 3 illustrates an individual to be decoded, where numbers 1, 2, and 3 represent agricultural machines $M_1$, $M_2$, and $M_3$, respectively. The operational farmland sets are $M_1=\{F_2, F_4\}$, $M_2=\{F_1\}$, and $M_3=\{F_3, F_5, F_6\}$, with the order of farmland operation being $M_1=\{F_4, F_2\}$, $M_2=\{F_1\}$, and $M_3=\{F_3, F_6, F_5\}$. The decoding process involves transforming the chromosome into a scheduling route using heuristic rules outlined in the algorithm. The first half of the genes assigns farmland to the corresponding agricultural machines, while the second half determines the order of farmland operation for each machine. The decoded sequence is presented in Figure 4.

(3) Initialize the population. The population is initialized by using the Nearest Neighbor Algorithm (NNC) to generate a set of high-quality feasible solutions, from which the optimal solution is selected as the initial solution for the NSGA-Ⅱ algorithm. The algorithm follows a greedy strategy, starting with a randomly

chosen farmland as the initial point. It then iterates through the unvisited farmlands, selecting the closest one to the current point as the next visited location and adding it to the path. This process continues until all farmlands have been visited, with the last visited farmland being connected back to the initial one to form a closed path. The resulting path is then converted into a chromosome representation.

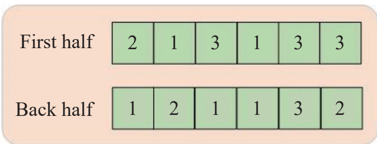



Figure 3 Examples of individuals to be decoded

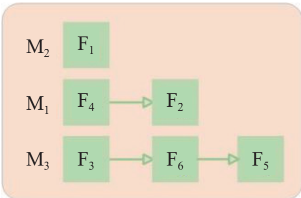



Figure 4 Sequence of operations for each farm field

(4) Fast undominated sorting and congestion calculation. Multi-objective functions often conflict with multi-objective optimization problems, necessitating the identification of superior solutions within the solution space. Non-dominated sorting categorizes individuals based on dominance relationships, assigning them to different levels of the frontier. An individual's frontier level indicates its quality; lower levels suggest greater superiority at the frontier. When comparing two individuals, the one with the lower level takes precedence. Crowding degree calculation involves using crowding distance to further evaluate individuals of the same rank. After determining dominance ranks, crowding distance calculation is necessary. In cases of identical frontier ranks, individuals with larger crowding distances are prioritized for non-dominance sorting. If two individuals have different frontier ranks, the one with the smaller rank is favored. In the event of equal frontier ranks, individuals with larger crowding distances are preferred.

$$\begin{cases} D(x,aim)=\dfrac{f_{aim}(x+1)-f_{aim}(x-1)}{f_{aim}^{\max}-f_{aim}^{\min}} \\ D(x)=\displaystyle\sum_{aim=1}^{k} D(x,aim) \end{cases} \tag{13}$$

where, $D(x, aim)$ represents the distance size of individual $x$ on target $aim$; $f_{aim}^{\max}$ and $f_{aim}^{\min}$ indicate the maximum and minimum values of target $aim$, respectively; $f_{aim}(x+1)$and $f_{aim}(x-1)$ refer to the neighboring values of individual $x$ under target $aim$; and $D(x)$ represents the size of the crowding distance of individual $x$, which is calculated as the sum of the distances of individual $x$ on each target. The crowding distances of the boundary points of each frontier are set to infinity. Non-dominated sorting and crowding degree operators are utilized in this research to hierarchically sort multiple solution sets, enabling the differentiation of the strengths and weaknesses of solution sets.

(5) Tournament selection. Tournament selection is utilized to prevent premature convergence to a local optimal solution by maintaining population diversity. This method involves randomly selecting two individuals to compete, comparing their ranks, and selecting the one with the lower rank. If the ranks are the same, their crowding degrees are compared, and the individual with the higher crowding degree is selected. This process is repeated multiple times to form a new population, leading to the renewal of the population. By continuously selecting better adapted individuals based on their rank and crowding degree, a new population is formed through competitive selection. This approach helps preserve and pass on good individuals to the next generation, ultimately promoting population evolution and optimization.

(6) Crossing. In order to preserve the favorable traits of the parent generation, new individuals are generated to explore different solutions within the population space. This study utilizes a crossover method that combines the first and second halves of the chromosomes. Specifically, the offspring individuals $C_1$ and $C_2$ are created by retaining position 2 from parent chromosome $P_1$ and sequentially inserting the remaining positions from parent chromosome $P_2$. Any illegitimate genes, such as inconsistencies in the number of farmland operated by agricultural machines or gene loci, are repaired using a random generation strategy. If illegitimate genes persist, the repair process is looped until all genes are legitimate. The crossover pattern is illustrated in Figure 5, while the repair process is shown in Figure 6. Table 2 presents the pseudo-code for the crossover pattern.

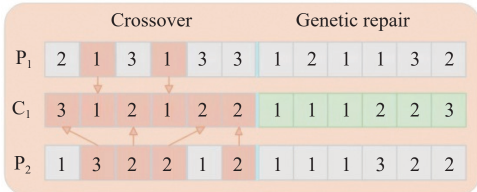



Figure 5 Cross-cutting patterns

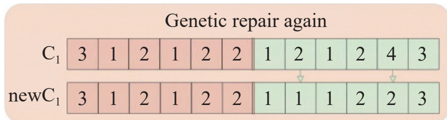



Figure 6 Repair process

**Table 2 Cross-modal pseudo-code**

| Algorithm: crossover mode | |
|---|---|
| Input | crossover($P_1$, $P_2$) |
| Output | [$C_1$, $C_2$] |
| | crossoverPoint = rand$i$([1, length($P_1$)/2]); |
| % Crossover of the first half of the chromosome | |
| | $C_1(i) = P_1(i)$; |
| | if $i$ ~= crossoverPoint; |
| | $C_1(i) = P_2(i)$; |
| | end |
| % Crossover of the second half of the chromosome | |
| | if $C_2(i)$ is an illegal gene |
| | $C_2(i)$ = generateRandomGene(); |
| | end |
| | return |
| | end |

(7) Mutation. Mutation plays a crucial role in enhancing the randomness and improving the search capability of algorithms. In traditional genetic algorithms, setting the mutation probability $P_m$ as a constant can lead to issues such as premature convergence and slow convergence towards the optimal solution. This paper proposes an enhanced mutation operator with an adaptive adjustment mechanism. Here, $f_{\max}$ represents the maximum fitness of the population, $f_{avg}$ denotes the average fitness of the population, $f$

stands for individual fitness, $P_{m2}$ indicates the minimum mutation probability, and $P_{m1}$ signifies the maximum mutation probability. The implementation process is outlined as follows:

$$P_m = \begin{cases} P_{m1} - \dfrac{(P_{m1} - P_{m2})(f_{\max} - f)}{f_{\max} - f_{avg}}, & f \geq f_{avg} \\ P_{m1}, & f < f_{avg} \end{cases} \tag{14}$$

(8) Simulated annealing operation. To address premature issues in traditional genetic algorithms, a neighborhood generation strategy based on crowding degree is proposed. This strategy reallocates the number of farmland operated by farm machines with high crowding degree to those with low crowding degree, thereby reducing conflicts. The congestion degree $c_i$ ($1 \leq i \leq m$) of a farm machine is defined as the length of the sequence of the number of farmland it operates. Initially, the crowding degree of all farm machines is calculated. A replacement for a high crowding degree farm machine $a_i$ ($1 \leq i \leq m$) is drawn using a roulette wheel with values based on crowding degree. Subsequently, a roulette wheel with values based on the inverse of crowding degree is used to select a low-crowding degree farm machine gene $a_j$ ($1 \leq j \leq m$). Finally, $a_i$ is replaced with $a_j$. The simulated annealing process, based on crowding degree, is illustrated in Figure 7. Following each generation of the NSGA-Ⅱ algorithm, individuals with the highest fitness are selected for simulated annealing. Initially, the temperature of simulated annealing is set for each extracted individual. The neighborhood generation strategy, based on crowding degree, is then used to generate a perturbed solution. The difference in fitness between the perturbed and original solutions is calculated. If the perturbed solution is superior, it is accepted; otherwise, the Metropolis criterion is applied to decide whether to accept the perturbed solution. This process continues with a gradual decrease in temperature until reaching the end temperature. Finally, the simulated annealed chromosomes are reintegrated into the original population.

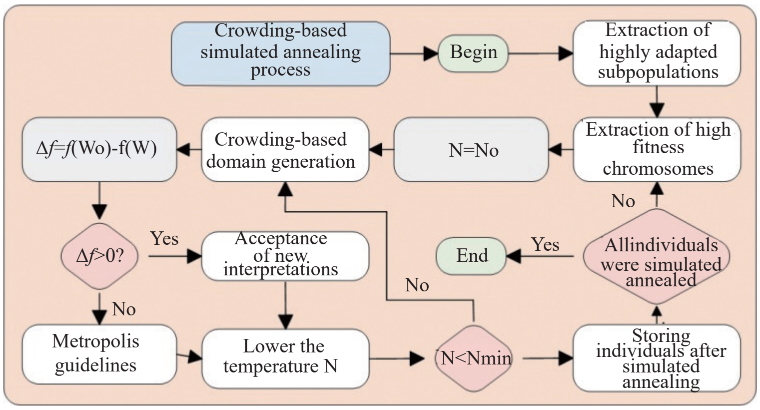



Figure 7 Crowding-based simulated annealing process

(9) Iterative evolution. The algorithm follows an iterative process to reach a specified number of generations. If the iterations meet the criteria, the algorithm stops and decodes the optimal result. If not, it continues iterating.

## 2.6 Clustering operation

In order to efficiently allocate farm machinery resources, farmland is assigned to each farm machinery cooperative using a clustering approach prior to scheduling. This chapter introduces a hybrid clustering algorithm designed to address complex constraints within the multi-region farm machinery scheduling model. The algorithm considers the spatial distribution and time window characteristics of operating points, as well as the matching rules for farm machine operations during each allocation process. Additionally, it includes a resource limitation check for farm machinery cooperatives. By transforming the problem of multiple farm machinery cooperatives into that of multiple single farm machinery cooperatives, the algorithm aims to optimize allocation. The basic framework of the clustering algorithm is illustrated in Figure 8, with the pseudo-code provided in Table 3.

TimeCloseness refers to the level of similarity between operating points and clusters within a specific time frame, while Closeness refers to the level of proximity between operating points and clusters in both time and space.

$$TimeCloseness(i,a) = \left\{ \frac{\sum_{j \in c(a) \cup \{a\}} e^{-(ATW(i,j)+TV_{ij})}}{|C|} \right\}, \quad a \in A, i, j \in C \tag{15}$$

where, $i$ represents an unplanned operation point, while $a$ denotes an agricultural cooperative. The set of agricultural cooperatives is denoted by $A$. For each $a \in A$, $C(a)$ represents the set of operation points assigned to the agricultural cooperative $a$. The symbol $TV_{ij}$ represents the transfer time between operation points $i$ and $j$. $ATW$ quantifies the distance between two operating points within a time window, calculated as follows: if the time windows do not overlap, $ATW$ equals the time interval between the closing of the previous

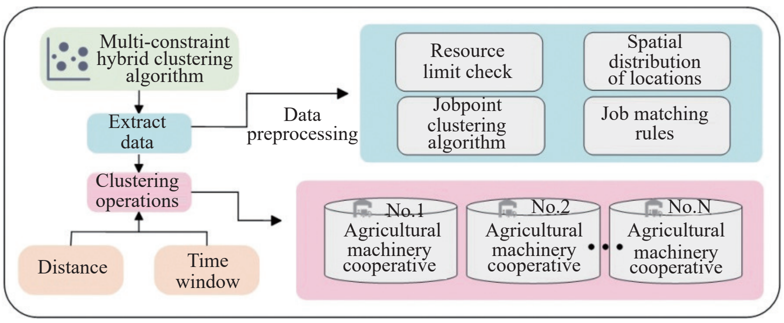



Figure 8 Flowchart of the multi-constraint hybrid clustering algorithm

window and the opening of the next. If there is an overlap, *ATW* is zero. The formula for Closeness is used to determine the assignment of operating points based on their calculated value.

**Table 3 Clustering algorithm pseudo-code**

| | Multi-constraint hybrid clustering algorithm |
|---|---|
| Input | data=readtable('coordinates.xlsx');<br>% Coordinates of farmland entrances and exits, agricultural cooperatives |
| Output | $A_1$=[];$A_2$=[];<br>% Number A indicates an agricultural cooperative |
| | Farmland_Center_Points=(import_Points+export_Points)/2; |
| | for $i$ = 1:length(farmland)<br>% Traversing each farmland |
| | distances=pdist2(Farmland_Center_Points, $A$); |
| | if checkTimeWindow(importPoint) &&<br>checkDistance(distances) &&<br>checkResourceLimit(resourceLimit) |
| | [~, centerIndex] = min(distances); |
| | assignedCenters(centerIndex).port = [assignedCenters(centerIndex).port; $i$]; |
| | end |
| | end |
| | checkTimeWindow(importPoint)<br>%Check time window constraints |
| | checkDistance(distances)<br>% Check distance constraints |
| | checkResourceLimit(resourceLimit)<br>% Check resource limitations |
| | return |
| | end |

$$\text{Closeness}(i,j)=\frac{a(i,j)}{\text{TimeCloseness}(i,j)},\quad j\in A, i\in C \tag{16}$$

Based on the Closeness function value, operating points can be prioritized in time and space distribution and then assigned to appropriate farm machinery cooperatives. It is crucial to ensure the allocation algorithm in each iteration meets the matching constraints of farm machinery operations and resource limitations. This involves checking if a farm machinery cooperative has machinery that can fulfill the operation requirements and if there are enough resources available to service the newly assigned operation point. If both conditions are satisfied, the allocation is accepted; otherwise, the process continues to the next operation point until all points are allocated or the cooperative's resources reach their limit.

## 3 Results and discussion

### 3.1 Experimental data

The farmland data collected for the experiments in this paper were obtained from the area near Bajiaojing, Anju District, Suining City, Sichuan Province, China. Experiments were conducted using LocaSpace Viewer software, specifically version 4.4.8.0, which integrates advanced technologies such as GPS and GIS. As illustrated in Figure 9, a total of thirty-five farmlands were selected, with the light green graphics representing the shape of the farmland, the green landmarks indicating the location of each farmland, and numbers 1-35 assigned to each farmland. For illustration purposes, two farm cooperatives were chosen, denoted by the letter $A$, with $A_1$ representing the first farm cooperative and $A_2$ representing the second, while the red landmarks indicate their locations. The experimental validation was conducted on the MATLAB 2022b platform, running on an i5-8250U CPU (1.60 GHz), with 8GB RAM, and under the Windows 10 operating system. The parameter settings of the improved NSGA-Ⅱ-SA algorithm can be found in Table 4.

Figure 9 Experimental area (created with LocaSpace Viewer, version 4.4.8.0, http://www.locaspace.cn/)

**Table 4 Improvement of NSGA-Ⅱ-SA algorithm parameter settings**

| Algorithm parameterization | |
|---|---|
| N_GENERATIONS ← 100 | % Number of iterations |
| POP_SIZE ← 50 | % Population size |
| ObjV_count ← 2 | % Number of targets |
| pc ← 0.9 | % Crossover probability |
| pm ← 0.05 | % Variation probability |
| GGAP ← 0.9 | % Generation gap |
| MaxOutIter ← 300 | % Maximum number of iterations of the outer loop |
| MaxInIter ← 15 | % Maximum number of iterations of the inner loop |
| T0 ← 0.025 | % Initial temperature |
| Alpha ← 0.99 | % Cooling factor |
| pSwap ← 0.2 | % Probability of choosing an exchange structure |
| pReversion ← 0.5 | % Probability of choosing a reversal structure |
| pInsertion ← 0.3 | % Probability of choosing an insertion structure |
| $x_1$ ← 8000 | % Start-up cost |
| Alpha ← 1000 | % Capacity violation penalty factor |
| Beta ← 100 | % Penalty factor for time window violations |

In the context of fertilizer application, there are a total of 16 fertilizer spreaders, with eight belonging to the $A_1$ agricultural cooperative and the remaining eight to the $A_2$ cooperative. The task at hand involves applying fertilizer to 35 farmlands using these spreaders. Table 5 provides essential details about the spreaders, such as their number, model, capacity, driving mode, and spraying range.

**Table 5 Selected agricultural machine models**

| Name | Quantity | Model | Volume/ $m^3$ | Spreading range/m |
|---|---|---|---|---|
| Taian Yimet 2FYP liquid fertilizer spreader | 6 | 2FYP | 8 | 7 |
| Shandong Tiansheng 2FYP-10 liquid fertilizer spreader | 5 | 2FYP-10 | 10 | 7 |
| Shunyuan 2YSP-8 fertilizer spreader | 5 | 2YSP-8 | 7 | 7 |

The algorithm's validation data is derived from actual farmland information and operational parameters, as depicted in Table 6. This table includes the coordinates of farm machinery cooperatives, entrance and exit points of farmlands, time windows, demand, operation duration, and farmland areas. By considering the spatial distribution and time constraints, the farmlands are categorized and allocated to the cooperatives, as listed in Table 7.

**Table 6 Data and information on agricultural cooperatives and farmland**

| Serial No. | Entrance | | Exit | | Area/hm² | Demand/m³ | Operation time/h | Time window |
|---|---|---|---|---|---|---|---|---|
| | Longitude | Latitude | Longitude | Latitude | | | | |
| $A_1$ | 105°32′17.18″ | 30°14′50.35″ | / | / | / | / | / | [0,1000] |
| $A_2$ | 105°32′50.05″ | 30°14′53.43″ | / | / | / | | / | [0,1000] |
| 1 | 105°32′24.93″ | 30°14′57.80″ | 105°32′23.42″ | 30°15′03.72″ | 1.0273 | 1 | 0.5 | [50,380] |
| 2 | 105°32′37.39″ | 30°15′00.69″ | 105°32′38.70″ | 30°15′03.96″ | 0.8715 | 0.9 | 0.4 | [109,239] |
| 3 | 105°32′27.27″ | 30°14′51.21″ | 105°32′24.80″ | 30°14′55.12″ | 1.1169 | 1.1 | 0.6 | [60,771] |
| 4 | 105°32′34.21″ | 30°14′46.73″ | 105°32′36.52″ | 30°14′49.50″ | 0.9266 | 0.9 | 0.4 | [141,571] |
| 5 | 105°32′23.67″ | 30°14′44.96″ | 105°32′27.15″ | 30°14′40.64″ | 1.6113 | 1.6 | 0.8 | [41,271] |
| 6 | 105°32′51.25″ | 30°14′46.95″ | 105°32′55.09″ | 30°14′43.22″ | 0.8793 | 0.9 | 0.4 | [95,625] |
| 7 | 105°32′32.40″ | 30°14′32.27″ | 105°32′34.81″ | 30°14′37.45″ | 1.7891 | 1.8 | 0.9 | [91,321] |
| 8 | 105°32′55.90″ | 30°14′39.20″ | 105°32′55.26″ | 30°14′34.61″ | 1.0648 | 1.1 | 0.6 | [91,521] |
| 9 | 105°32′17.92″ | 30°14′32.59″ | 105°32′21.66″ | 30°14′28.93″ | 0.9707 | 1 | 0.6 | [119,749] |
| 10 | 105°32′54.40″ | 30°14′59.11″ | 105°32′53.98″ | 30°14′55.80″ | 0.5014 | 0.5 | 0.3 | [59,389] |
| 11 | 105°32′07.64″ | 30°14′52.10″ | 105°32′05.74″ | 30°14′56.06″ | 0.9611 | 1 | 0.5 | [64,294] |
| 12 | 105°32′04.52″ | 30°14′41.94″ | 105°32′06.58″ | 30°14′39.02″ | 0.5393 | 0.5 | 0.3 | [142,772] |
| 13 | 105°32′44.42″ | 30°14′39.88″ | 105°32′47.88″ | 30°14′42.54″ | 0.7091 | 0.7 | 0.4 | [35,655] |
| 14 | 105°32′17.19″ | 30°14′59.35″ | 105°32′19.74″ | 30°15′05.34″ | 1.2568 | 1.3 | 0.7 | [58,888] |
| 15 | 105°32′09.74″ | 30°14′48.48″ | 105°32′12.18″ | 30°14′46.91″ | 0.2198 | 2 | 1 | [72,702] |
| 16 | 105°32′31.78″ | 30°15′03.91″ | 105°32′28.99″ | 30°15′08.22″ | 1.0557 | 1.1 | 0.6 | [149,979] |
| 17 | 105°32′11.42″ | 30°15′01.92″ | 105°32′07.64″ | 30°15′05.31″ | 1.0403 | 1 | 0.5 | [388,911] |
| 18 | 105°31′58.71″ | 30°15′00.35″ | 105°32′01.30″ | 30°15′02.81″ | 0.5115 | 0.5 | 0.3 | [30,546] |
| 19 | 105°32′17.11″ | 30°14′36.24″ | 105°32′16.79″ | 30°14′38.52″ | 0.1932 | 0.2 | 0.1 | [353,708] |
| 20 | 105°32′01.09″ | 30°14′45.19″ | 105°31′56.48″ | 30°14′46.76″ | 0.5847 | 0.6 | 0.3 | [425,913] |
| 21 | 105°32′01.98″ | 30°14′35.11″ | 105°32′03.09″ | 30°14′36.81″ | 0.2330 | 0.2 | 0.1 | [40,630] |
| 22 | 105°32′41.19″ | 30°14′54.80″ | 105°32′39.74″ | 30°14′56.58″ | 0.2238 | 0.2 | 0.1 | [228,667] |
| 23 | 105°32′47.62″ | 30°15′02.47″ | 105°32′46.45″ | 30°15′04.57″ | 0.3323 | 0.3 | 0.2 | [161,558] |
| 24 | 105°32′35.27″ | 30°14′54.97″ | 105°32′33.64″ | 30°14′58.00″ | 0.4672 | 0.5 | 0.3 | [229,624] |
| 25 | 105°32′45.51″ | 30°14′56.90″ | 105°32′45.74″ | 30°14′59.12″ | 0.2314 | 0.2 | 0.1 | [213,648] |
| 26 | 105°32′48.20″ | 30°14′46.91″ | 105°32′47.69″ | 30°14′47.98″ | 0.3264 | 0.3 | 0.2 | [404,753] |
| 27 | 105°31′51.09″ | 30°14′49.63″ | 105°31′51.35″ | 30°14′51.31″ | 0.1998 | 0.2 | 0.1 | [33,511] |
| 28 | 105°31′55.00″ | 30°14′58.09″ | 105°31′53.35″ | 30°14′52.20″ | 0.5010 | 0.5 | 0.3 | [46,519] |
| 29 | 105°32′47.40″ | 30°14′35.34″ | 105°32′56.07″ | 30°14′31.00″ | 0.9700 | 1 | 0.5 | [395,911] |
| 30 | 105°31′49.15″ | 30°15′08.30″ | 105°31′51.24″ | 30°15′04.94″ | 0.5558 | 0.6 | 0.3 | [35,697] |
| 31 | 105°32′40.89″ | 30°15′09.09″ | 105°32′40.17″ | 30°15′11.14″ | 0.4037 | 0.4 | 0.2 | [39,528] |
| 32 | 105°32′00.58″ | 30°15′08.28″ | 105°31′59.34″ | 30°15′10.94″ | 0.4743 | 0.5 | 0.3 | [94,535] |
| 33 | 105°32′57.56″ | 30°14′48.46″ | 105°32′59.46″ | 30°14′46.20″ | 0.3368 | 0.3 | 0.2 | [394,909] |
| 34 | 105°31′57.08″ | 30°14′39.47″ | 105°31′56.74″ | 30°14′40.66″ | 0.2161 | 0.2 | 0.1 | [218,571] |
| 35 | 105°31′54.05″ | 30°14′33.27″ | 105°31′54.78″ | 30°14′36.76″ | 0.4588 | 0.5 | 0.3 | [85,542] |

**Table 7 Clustering results**

| Center No. | Farmland No. |
|---|---|
| $A_1$ | 1, 3, 5, 7, 9, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 27, 28, 30, 32, 34, 35 |
| $A_2$ | 2, 4, 6, 8, 10, 13, 22, 23, 24, 25, 26, 29, 31, 33 |

### 3.2 Research on field scheduling algorithms

3.2.1 Full-coverage path planning algorithm

In order to optimize scheduling operations and minimize costs, it is crucial to consider the paths taken during in-field operations. Achieving a high coverage rate involves prioritizing the shortest distance and time possible. Research indicates that reducing in-field operation time can effectively decrease scheduling time. To achieve the quickest completion time for full-coverage farm operations, it is recommended to minimize the number of turns by planning the path along the longest side[29]. To enhance control and reduce heavy plowing and missed areas, this study adopts a reciprocating mulching operation mode, with turning mode selection based on minimum turning radius and width constraints[30,31]. The path planning process, illustrated in Figure 10, presents two routes for scheduling agricultural machines to $A_1$ and $A_2$ agricultural cooperatives. By implementing full-coverage path planning starting from the longest side and making informed decisions on turning, the actual operation time in the field is detailed in Table 6. Table 8 provides parameter settings, including reference coordinate origin, minimum turning radius, operating width, field width, and rolling friction coefficient.

3.2.2 Study on optimal traversal order based on multiple farmlands

To validate the effectiveness and superiority of the improved NSGA-Ⅱ-SA hybrid algorithm, it was compared with the NSGA-Ⅱ-SA hybrid algorithm from literature [32], the improved NSGA-Ⅱ algorithm from literature [33], and the PSOSA hybrid algorithm from literature [34]. Each algorithm was separately tested and the optimal roadmap was generated. The optimal routing diagrams produced by the improved NSGA-Ⅱ-SA algorithm, the standard NSGA-Ⅱ-SA algorithm, the enhanced NSGA-Ⅱ algorithm, and the PSOSA algorithm are shown in Figures 11a-11d, respectively. The letter “*R*” denotes a scheduling scheme, and the detailed routing schedules are provided in Table 9.

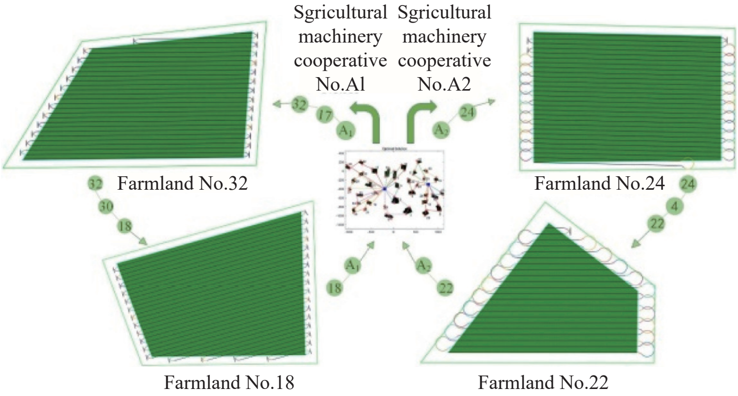


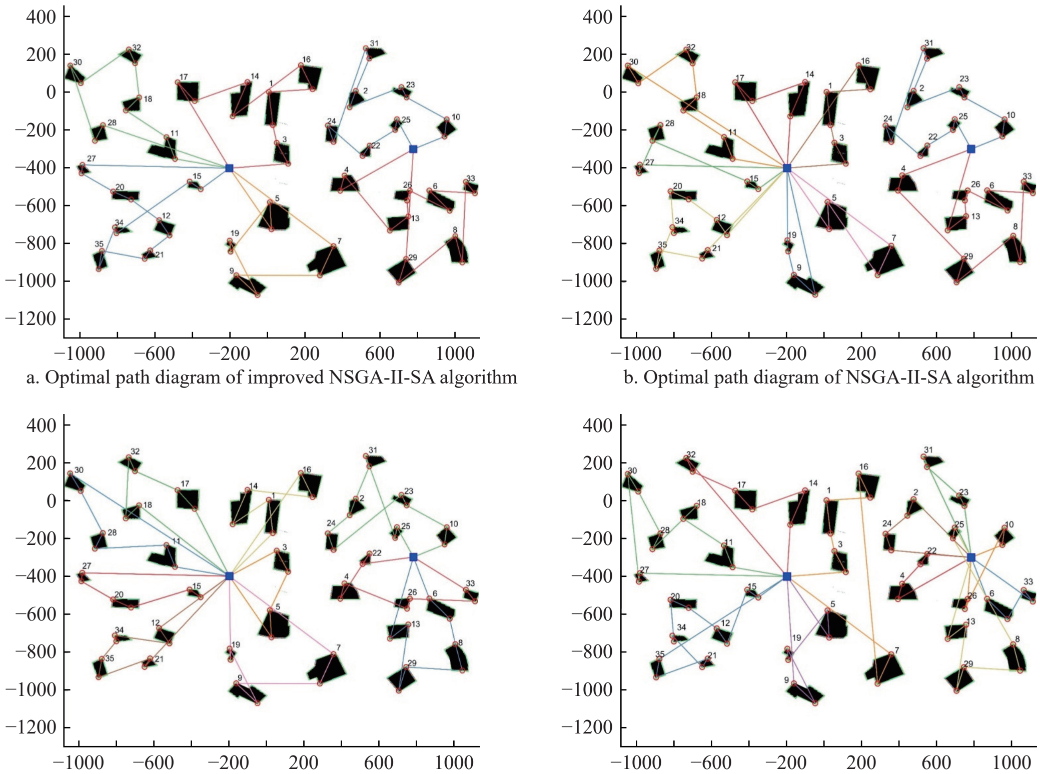

Figure 10 Road map to full coverage

**Table 8 Parameter settings**

| Coordinate reference point | Minimum turning radius/m | Working width/m | Headland width/m | Coefficient of rolling friction |
|---|---|---|---|---|
| (105°32′17.19″,30°14′59.35″) | 2.4 | 2 | 3 | 0.1 |

The comparison experiments of the four algorithm routes revealed that farm machines from the nearest farm machinery cooperatives are scheduled to operate on all farmlands within the specified operation time. The roadmap outlined in Table 9 demonstrates that each route commences from the closest agricultural machinery cooperatives to the farmland. The algorithm proposed in this study minimizes the number of agricultural machines required, resulting in lower transfer costs compared to other algorithms. Moreover, the algorithm calls for significantly fewer agricultural machines than the total available at the cooperatives, effectively meeting the farmers' order requirements.

The study evaluates the performance of the Improved NSGA-Ⅱ-SA algorithm by conducting comparison experiments with algorithms from literature [32-34]. The results in Figure 12 and 13 indicate that the algorithms from literature [32-34] tend to converge to local optima, while the Improved NSGA-Ⅱ-SA algorithm proposed in this paper achieves superior results in terms of convergence speed and global optimization, outperforming the other algorithms. Data analysis presented in Table 10 shows that the Improved NSGA-Ⅱ-SA algorithm significantly outperforms the other algorithms in terms of total scheduling cost, scheduling time, and the number of farm machines scheduled. The algorithm in this paper provides better farm machine scheduling solutions and faster convergence to optimal solutions, reducing total scheduling costs by 9.8%, 3.1%, and 8.7%, and total scheduling time by 12.5%, 13.4%, and 11.6% compared to the other three algorithms, respectively. These results demonstrate the effectiveness and superiority of the Improved NSGA-Ⅱ-SA algorithm for multi-region scheduling of agricultural machines in hilly and mountainous areas, meeting the scheduling requirements effectively.



a. Optimal path diagram of improved NSGA-II-SA algorithm

b. Optimal path diagram of NSGA-II-SA algorithm

c. Optimal path diagram of improved NSGA-II algorithm

d. Optimal path diagram of PSOSA algorithm

Figure 11 Optimal path diagram of different algorithms

**Table 9 Scheduling routes for each piece of agricultural machinery**

| Arithmetic | Agricultural machinery cooperative No. | Route |
|---|---|---|
| Improved NSGA-Ⅱ-SA | $A_1$ | $R1$: $A_1$→15→34→35→21→12→20→27→$A_1$<br>$R2$: $A_1$→3→1→16→14→17→$A_1$<br>$R3$: $A_1$→11→18→32→30→28→$A_1$<br>$R4$: $A_1$→5→19→9→7→$A_1$ |
| | $A_2$ | $R1$: $A_2$→10→23→2→31→24→22→25→>$A_2$<br>$R2$: $A_2$→4→13→26→6→33→8→29→$A_2$ |
| Ref [32] | $A_1$ | $R1$: $A_1$→15→20→27→$A_1$<br>$R2$: $A_1$→11→28→30→$A_1$<br>$R3$: $A_1$→17→32 → 18→$A_1$<br>$R4$: $A_1$→5→3→$A_1$<br>$R5$: $A_1$→1→14→16→$A_1$<br>$R6$: $A_1$→21→35→34→12→$A_1$<br>$R7$: $A_1$→19→9→7→$A_1$ |
| | $A_2$ | $R1$: $A_2$→13→29→8→6→$A_2$<br>$R2$: $A_2$→22→4 → 26→33→$A_2$<br>$R3$: $A_2$→10→23→24→2→31→25→$A_2$ |
| Ref [33] | $A_1$ | $R1$: $A_1$→14→17→$A_1$<br>$R2$: $A_1$ → 9→19→$A_1$<br>$R3$: $A_1$→15→28→27->$A_1$<br>$R4$: $A_1$→11→18→32→30→$A_1$<br>$R5$: $A_1$→12→20→34→35→21→$A_1$<br>$R6$: $A_1$→3→1→16→$A_1$<br>$R7$: $A_1$→5→7→$A_1$ |
| | $A_2$ | $R1$: $A_2$→10→23→2→31→24→22→25→$A_2$<br>$R2$: $A_2$→13→26→6→33→8→29→4→$A_2$ |
| Ref [34] | $A_1$ | $R1$: $A_1$→15→12→20→34→21→35→$A_1$<br>$R2$: $A_1$→14→17→32→$A_1$<br>$R3$: $A_1$→11→18→28→30→27→$A_1$<br>$R4$: $A_1$→3→1→16→7→$A_1$<br>$R5$: $A_1$→5→19→9→$A_1$ |
| | $A_2$ | $R1$: $A_2$→4→22→$A_2$<br>$R2$: $A_2$→33→6→$A_2$<br>$R3$: $A_2$→23->31→$A_2$<br>$R4$: $A_2$→10→26→$A_2$<br>$R5$: $A_2$→13->29→8→25→$A_2$<br>$R6$: $A_2$→24→2→$A_2$ |

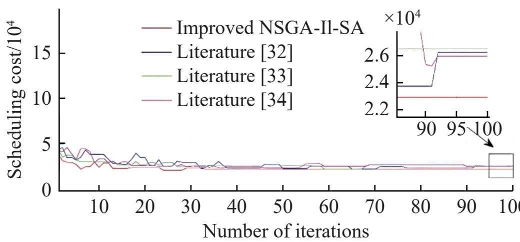



Figure 12 Comparative time-analysis experiments

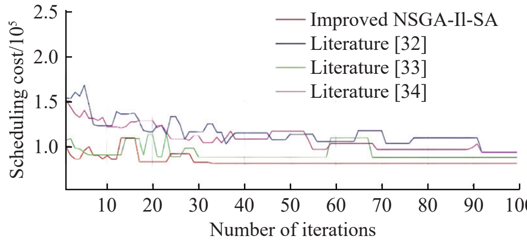



Figure 13 Cost comparison analysis experiment

**Table 10 Comparison of scheduling results**

| Algorithms | Number of agricultural machines | Total time/s | Total scheduling costs/CNY |
|---|---|---|---|
| Improved NSGA-Ⅱ-SA | 6 | 22 923.6 | 81 496.2 |
| Ref [32] | 10 | 26 193.3 | 90 384.1 |
| Ref [33] | 9 | 26 467.3 | 84 126.4 |
| Ref [34] | 11 | 25 924.6 | 89 229.3 |

## 4 System design

This chapter outlines the design and implementation of a web-based multi-region farm machinery scheduling system. The user interface integrates front-end technologies like HTML, CSS, and JavaScript, along with Python's Django framework and a back-end database to support essential functions such as farm machinery management, route planning, task assignment, and back-end task management, as depicted in Figure 14. The system is designed to offer an intuitive and user-friendly platform for both farmers and farm machinery schedulers. Users can effectively oversee farm machinery resources, strategize operation routes, and monitor real-time operation progress and impact.

The system interface consists of four main modules: homepage, order, operation management, and setting. The focal point of the front-end system is the Home Page, which offers users a quick overview of the simulation platform. The Home Page features a concise introduction to the platform's goals, functional aspects, and usage instructions, facilitating users in grasping the platform's fundamentals and operational procedures efficiently. Along with the introduction, the Home Page incorporates a map display feature that leverages HTML5's Canvas or SVG technology, JavaScript, and the map service provider's API to import and showcase the region's map. Users can easily identify the farmland to be operated and the distribution of agricultural cooperatives on the map. Moreover, the system provides real-time updates on the online and offline status of farm machinery, current operating area, time, and other relevant


Figure 14 Agricultural machinery scheduling system interface diagram

information. To cater to users' detailed information needs regarding farm machinery operations, the order module enables users to view and manage all farm machinery operation orders, including order status, operation area, and farm machinery distribution. The operation management module aims to enhance users' understanding of farm machinery usage and operational outcomes, offering comprehensive management functions for farm machinery and cooperatives. Users can add, edit, and delete farm machinery and cooperative information within this module. Lastly, the setting module empowers users to configure and adjust various system parameters to suit diverse user requirements.

Through practical application validation, the system demonstrates significant practical value and broad application potential, providing an efficient and practical solution for scheduling farm machinery.

## 5 Discussion

Traditional algorithms often struggle to effectively solve complex NP-hard problems due to poor global convergence, leading to suboptimal results. In agricultural production, especially during busy seasons and under uncertain weather conditions, efficient and precise scheduling of unmanned machinery across multiple farmlands and time scales is essential. To address these challenges, this study applies a multi-objective optimization algorithm capable of balancing multiple conflicting goals, improving both resource allocation and fertilizer application efficiency. Comparative experiments with methods from [32-34], supported by repeated trials, show that the proposed algorithm achieves lower scheduling costs and reduced operation times (Tables 9 and 10), demonstrating superior performance and adaptability in multi-region, multi-timescale agricultural machinery scheduling.

## 6 Conclusions

(1) This study addresses the challenge of scheduling multi-region farmland in hilly and mountainous areas with a focus on minimizing scheduling costs and time. A multi-region farm machinery scheduling model is developed, along with an enhanced NSGA-Ⅱ-SA algorithm to tackle the problem. The effectiveness and superiority of the model and algorithm are demonstrated through practical examples.

(2) Additionally, a web-based multiregional farm machinery scheduling system is designed, featuring modules for homepage, order, operating management, and settings. The system facilitates farm machinery management, route planning, and task assignment, offering practical utility and ease of operation.

(3) The experimental results demonstrate that the optimization strategy of the enhanced NSGA-Ⅱ-SA algorithm offers benefits in reducing both scheduling costs and the number of scheduled farm machines. Specifically, the improved NSGA-Ⅱ-SA algorithm achieves the lowest number of scheduled farm machines and reduces total scheduling costs by 9.8%, 3.1%, and 8.7% compared to other algorithms. Moreover, it decreases total scheduling time by 12.5%, 13.4%, 11.6%, and 13.4% compared to alternative algorithms, with reductions of 13.4% and 11.6% in different scenarios. This approach proves to be economically viable, ensuring the rationality of final scheduling, validating the effectiveness and superiority of the agricultural machine scheduling model and solution algorithm. It is adept at meeting the demands of multi-region scheduling in the intricate terrain of hilly and mountainous areas.

(4) In summary, the need for multiple fertilizations throughout the growth and maturity of crops, which occur at various time scales, highlights the importance of fertilizer application management in agricultural production. Therefore, a thorough investigation into multi-region agricultural machinery scheduling holds significant practical significance and theoretical value in optimizing resource allocation, improving fertilizer application efficiency, and advancing sustainable development in agricultural production.


## Acknowledgements

This work was supported in part by the Research on Autonomous Precision Operation and Path Planning of Unmanned Agricultural Machine (Grant No. Z222057), Research on Agricultural Machine Scheduling Methods and System Design Under Complex Land Conditions in Hilly and Mountainous Areas (Grant No. XDNY2023-001), and Remote Control Electric Potato Planter Development (Grant No. 232206-1).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