Computers and Electronics in Agriculture 232 (2025) 110060

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

A collaborative scheduling and planning method for multiple machines in harvesting and transportation operations-Part I: Harvester task allocation and sequence optimization☆

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ARTICLE INFO

Keywords:
Agricultural machine
Collaborative scheduling
Scheduling model
Electronic map
Path planning

ABSTRACT

In the scenario of harvesting-transportation operation, the collaborative scheduling of harvesters and grain trucks is crucial for addressing the challenge of scheduling different types of agricultural machinery in farm areas. During the harvest, the harvesters and grain trucks must cooperate within a short time window. This study is divided into two parts (Part I and Part II), focusing on the collaborative scheduling problem of the harvesters, and operation coordination between harvesters and grain trucks, respectively. In this paper (Part I), we focus on addressing the problem of harvester task allocation and path planning. First, the topological map method was used to define the topological structure and construct an electronic map of the farm. Then, a multi-harvester task allocation model was built, and a greedy minimum–maximum load balancing algorithm based on the nearest-neighbor heuristic (GMM-LB-NNH) algorithm was proposed to solve the model and obtain the task sequence for the harvesters. Finally, based on the task sequence, the whole-process path planning for the harvester was completed. We conducted simulation tests of harvester task allocation and whole-process path planning experiments for harvesters using the electronic map we developed. The results demonstrate that the proposed method effectively achieves harvester task allocation and path planning. Additionally, it significantly reduces overall operation time by an average of 29.8 min compared to the Ant Colony Optimization algorithm and by 12.6 min compared to the Genetic Algorithm, providing a novel approach for the scheduling and planning of the same types of agricultural machinery.

1. Introduction

With the development of China's socio-economic conditions and the intensification of population aging, a large number of young rural laborers have migrated to cities, resulting in an irrational agricultural labor structure mainly relying on middle-aged and elderly workers with generally low technical levels, causing agriculture to face a labor shortage. The physical strength and work efficiency of older people are relatively low, making it difficult for them to perform heavy agricultural work, which further affects the efficiency and quality of agricultural production (Ji et al., 2024; Ren et al., 2023). Many laborers in the farming sector lack skills in operating modern farm machinery and technical support, making it difficult to utilize modern agricultural machinery to improve production efficiency effectively. As the labor supply decreases, agricultural labor costs gradually rise, increasing the economic burden on agricultural producers (Lu et al., 2019). Therefore, developing smart agriculture and unmanned farms has become a primary means to reduce dependence on labor and address the problem of labor shortages.

With the comprehensive deployment of China's Beidou Navigation Satellite System (BDS) (Radočaj et al., 2023; Zhang et al., 2022a), automatic navigation of agricultural machinery has become a critical

☆ This article is part of a special issue entitled: 'Sust. Agri. 4.0' published in Computers and Electronics in Agriculture.

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https://doi.org/10.1016/j.compag.2025.110060
Received 5 December 2024; Received in revised form 29 January 2025; Accepted 29 January 2025
Available online 12 February 2025

factor in promoting the development of smart agriculture, and unmanned agricultural machinery is being applied to all stages of agricultural production (Yao et al., 2024; Xie et al., 2023). The multi-machine collaborative operation mode, where multiple agricultural machines work in the plots, has become the focus of research on unmanned farms and regional farmland machinery operations, especially in terms of unmanned operation and scheduling management of agricultural machinery equipment (Karunathilake et al., 2023; Yousaf et al., 2022). Replacing humans with intelligent equipment can reduce labor intensity and improve work quality. Multi-machine collaborative operations can significantly improve agricultural production efficiency and effectively address urgent harvesting and planting emergencies (Ji et al., 2023; Lu et al., 2023a). Among them, multi-machine collaborative scheduling planning is the core technology of multi-machine collaborative operations, which can achieve coordinated scheduling and management of multiple machines to improve agricultural production efficiency and reduce production costs.

Collaborative scheduling and planning methods for agricultural machines are mainly divided into scheduling the same type of machines and different types of machines depending on the operation needs in different production scenarios (Wang et al., 2024; Gao et al., 2021). For example, the scheduling of harvesters in harvesting operations belongs to the domain of scheduling of the same type of machines, which is the research focus of Part I of this study (this paper). The scheduling of harvesters and grain trucks in harvesting operations belongs to the domain of scheduling of different types of machines, which is the research focus of Part II (He et al., 2021; Zhu et al., 2024). Reasonable scheduling and planning of multiple machines of the same type can improve the entire system's efficiency and reduce execution costs. For example, to harvest several plots distributed in different areas of the farm, how to optimize the task allocation and path planning for multiple harvesters to achieve the highest efficiency will be a challenge.

In addressing the task allocation problem in multi-machine operations, current methodologies predominantly rely on intelligent optimization algorithms, including heuristic search algorithms (Agrawal et al., 2014), genetic algorithms (Zhong et al., 2023), ant colony optimization (Wang et al., 2023), and particle swarm optimization (Li et al., 2021a). These optimization methods utilize mathematical models and problem constraints, employing convergence techniques to explore the entire solution space. These approaches are capable of converging to suboptimal solutions, with a certain probability of identifying the optimal solution. Previous research in solving task allocation problems with various algorithms has largely focused on enhancing the performance of these algorithms, particularly in improving efficiency and addressing the challenge of obtaining the optimal solution (Li et al., 2022). As the number of machines and tasks increases, many of these algorithms face difficulties in effectively scaling to accommodate larger, more complex scenarios. The task complexity in multi-machine agricultural operations is highly variable, and many algorithms struggle to account for this diversity, resulting in suboptimal task allocation.

In summary, the aim of this paper is to achieve collaborative scheduling of multiple agricultural machines, focusing on harvester task allocation and path planning, which falls under the category of scheduling and planning for same types of agricultural machinery. The primary contributions of this paper are:

(1) To establish and solve a multi-harvester task allocation model based on the established farm map to minimize the overall operation time of the harvesters.
(2) To perform the whole process path planning (path planning within and between fields) for the harvesters based on the task sequence and the actual map.
(3) Through applying the proposed method on two actual farms, to evaluate the performance of the algorithm and the feasibility of this method through comparison with other algorithms and scheduling instances.

The organization of the paper is as follows: Section 2 presents a framework for collaborative scheduling and planning methods for multiple machines. It introduces the problem description, outlines the application scenarios for the model, and discusses the assumptions underlying the model. Section 3 covers the construction and solutions of scheduling models, including the development of the electronic farm map, the allocation and optimization of harvester tasks and sequences, and the whole-process path planning of the harvester. Section 4 presents the results from simulation experiments. Finally, Section 5 offers conclusions and suggests directions for future work.

2. Related work

Task allocation and path planning are two key components of collaborative scheduling and planning methods for agricultural machines. Both domestic and international scholars have made some progress in multi-machine collaborative task allocation. In recent years, research on task allocation of agricultural machines is more focused on the same types of agricultural machines.

For example, Lu et al. (2023b) formulated the agricultural multi-robot task allocation problem as a multi-objective multiple traveling salesman problem (MO-MTSP) and applied an improved version of the non-dominated sorting genetic algorithm (INSGA-II) to solve it. The allocation plan was dynamically adjusted in real-time by continuously monitoring the status of the robots and tasks. The results demonstrate that the improved algorithm effectively enhances task allocation in multi-robot agricultural systems. Similarly, Cao et al. (2021) combined dynamic task allocation with static task allocation to establish a task allocation model for multi-machine collaboration and used an improved ant colony algorithm to solve the model. Experimental results showed that the improved ant colony algorithm effectively reduces path costs. Ma et al. (2022) established an agricultural machinery scheduling model under dynamic demand based on order resource and agricultural machinery resource sharing and solved the scheduling model by using a hybrid heuristic algorithm. Through simulation verification and analysis of a rice harvesting operation in Wuchang City, the results demonstrated the effectiveness and feasibility of the scheduling strategy.

The abovementioned studies have addressed task allocation and obtaining a task sequence. However, few studies have been conducted about path planning under task allocation, which is essential for determining the operational path of agricultural machinery (Li et al., 2023a). Wu et al. (2024) proposed a static task allocation model for rice harvesting in small fields in hilly and mountainous regions. They employed the Optimal Gene Fragment Retention method based on Genetic Algorithm (OGFR-GA) and the Multi-Loop Weighted Connected Graphs based on Prim's algorithm (MLW-Prim) to solve the problem. The results indicated that the combined model of OGFR-GA and MLW-Prim reduced the number of iterations required to reach the optimal solution by approximately 45 %, and reduced costs by 1.2 % to 6.9 %. While the model comprehensively considers factors such as operational paths and time, the study primarily addresses the connection paths between tasks and does not take into account the internal rice harvesting paths within each task. Lu et al. (2024) focused on the task allocation problem for agricultural multi-robot systems, aiming to minimize the maximum operational time of the sub-robots. They constructed a task allocation model and proposed a Reinforcement Learning-based Attention Mechanism Policy Optimization Network (NWC-APONet) method to determine the optimal allocation scheme. Experimental results demonstrated the practical applicability and effectiveness of this model in the context of agricultural multi-robot task allocation. This approach considers both internal paths within plots and inter-plot paths during the allocation process. However, in the calculation of inter-plot paths, plots are treated as nodes, which overlook the actual transfer routes on the farm and the start and end points of the internal coverage paths, resulting in an incomplete path that is not fully suitable for navigation tasks. Additionally, there is a lack of integration with agricultural applications and limited practical implementation, and the models are relatively simple (Li et al., 2021b; Liu et al., 2022; Li et al., 2024).

Despite the numerous effective methods researchers propose for task allocation and path planning, these approaches still exhibit certain limitations. For instance, the methods above fail to adequately address issues such as task load balancing and multi-agricultural machine operations in real-world agricultural environments, thus rendering them inadequate for handling more complex practical multi-machine collaborative operations. Furthermore, for a comprehensive multi-machine operation problem, integrating both task allocation and path planning is essential to achieve superior practical application outcomes. To tackle these challenges, we have proposed a novel method to manage the scheduling issue of harvesters in the context of harvesting and transportation. This method enables the collaborative scheduling and path planning of harvesters in harvesting-transportation scenarios. It effectively reduces overall operation time while demonstrating notable stability.

3. Organization of the two-part paper

This study is divided into two parts, and the structure of the paper is shown in Fig. 1. The first part introduces the task allocation and path planning of the harvester, using a topological map method to construct an electronic map of the farm. A multi-harvester task allocation model was established with the objective of minimizing the overall operation time of the harvesters. The greedy minimum–maximum load balancing algorithm based on the nearest-neighbor heuristic (GMM-LB-NNH) was proposed and used for task allocation and sequence optimization, resulting in the harvester's task sequence and whole-process path planning. Next, based on the obtained harvester task sequence, the second part focused on the collaborative scheduling of grain trucks. Based on the harvester path planning, the grain unloading points were generated using a generation and adjustment method. A collaborative scheduling model for grain trucks was built, and a hybrid genetic and heuristic iterative (HGHI) algorithm was used to schedule and plan the grain trucks. This results in the sequence of operating positions for the grain trucks, while also updating the harvester's operating time. Finally, the scheduling timetable for the harvesters and grain trucks was obtained.

(1) Constructing an electronic farm map

Constructing an electronic farm map is an important component of path planning, and accurate electronic map information is a prerequisite for operational path planning and agricultural machinery navigation. This paper integrated the latitude and longitude coordinates of the actual farms to carry out agricultural machinery scheduling planning, which is more conducive to the use of agricultural machinery navigation systems. Based on the known environmental map data, a specific mathematical model was used to describe the operational environment and to construct a digital map that is easy to identify and store. Using Zhuozhou Experimental Farm in Hebei Province and Qingpu Unmanned Eco-Farm in Shanghai as research bases, an electronic map was established using the topological map method.

(2) Harvester task allocation and sequence optimization

Harvester task allocation is based on task allocation for the same type of agricultural machinery and is characterized by multiple machines and tasks. A series of tasks must be allocated to specific agricultural machinery, enabling them to achieve high returns while completing all tasks (Cui et al., 2024). A multi-harvester task allocation model was constructed to achieve task allocation for multiple harvesters and to minimize overall operation time. A GMM-LB-NNH algorithm was used to solve the model, obtaining the task sequence and operational time for each harvester while also planning the entire operational path of the harvesters. In the task allocation scenario, this method can minimize the maximum load among resources while ensuring simplicity, efficiency, and adaptability, making it suitable for many practical applications.

(3) Generating and adjusting farmland unloading points

Determining the location of the grain unloading points is crucial for multi-machine scheduling. The grain trucks need to reach all unloading points to complete the grain loading, while the harvesters need to empty their grain tanks at the unloading points. The unloading points are the key connection between the harvesters and the grain trucks, making the generation of unloading points particularly important (Han et al., 2024). This paper adopted the method of unloading grain at the headland to generate and adjust the locations of the unloading points. Unloading grain at the headland means that the grain trucks do not need to enter

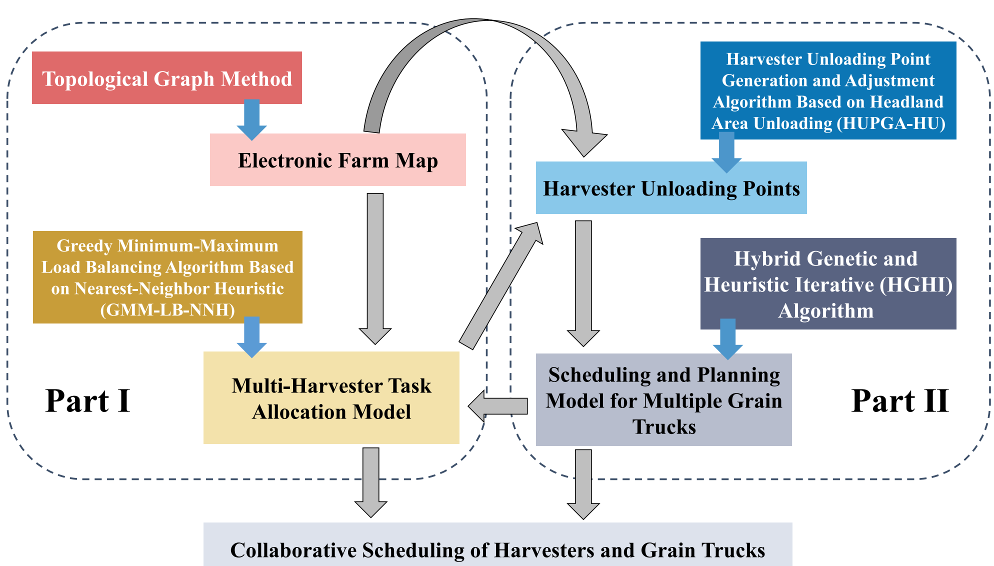

Fig. 1. Organization of the two-part paper.

the fields, allowing them to load grain directly at the headland, thereby reducing the operation paths of the trucks and improving efficiency.

(4) Scheduling and planning of grain trucks

The scheduling of grain trucks is based on the allocation of harvester tasks and the locations of unloading points, serving as a secondary scheduling on top of harvester scheduling (Li et al., 2023b). The scheduling results of the grain trucks will affect the waiting time of the harvesters, thus requiring updates to the harvester operation times. To achieve the scheduling and planning of multiple grain trucks, a multi-grain truck system scheduling model was constructed to minimize the total travel distance of all grain trucks and the total waiting time of all harvesters. An HGHI algorithm was used to solve the model, resulting in each grain truck's task location sequence and operation time. This combination fully utilized the global search capabilities of genetic algorithms and the local optimization advantages of heuristic methods, effectively solving the complex grain truck scheduling problem and providing a robust and effective solution for optimization challenges.

4. Construction of collaborative scheduling model for harvesters

4.1. Problem description

The collaboration between harvesters and grain trucks is a common scenario in agricultural production involving different types of machines, and studying it holds significant importance. In this scenario, the harvester is responsible for harvesting crops, while the grain truck is responsible for transporting the harvested grain to a designated site. Multiple harvesters operate across several fields, and when a harvester's grain tank is full, the grain transport truck accurately drives to the unloading point. Using a mechanical arm or conveyor belt, the harvester transfers the grain directly onto the grain truck. This process usually takes only a few minutes, significantly reducing the harvester's downtime and improving operational efficiency. The fully loaded grain truck delivers the crops to the farm's granary. After unloading, it proceeds to another unloading point to load more grain. Meanwhile, several other grain trucks are engaged in loading, transferring, and unloading grain-related tasks. This seamless transportation method ensures that the harvesters can operate continuously, avoiding downtime caused by waiting for grain trucks and thereby improving overall operational efficiency.

This problem considers multiple agricultural machines (harvesters and grain trucks) providing regional harvesting services for several wheat fields awaiting harvest, including the number of harvesters and grain trucks deployed in each operation. Each field awaiting operation can be regarded as a task unit, and the model comprehensively considers the transport paths between the storage and the task units, as well as the transport and coverage paths within the task units.

Due to the complex and variable field operation environment in the region, we defined the basic assumptions of the harvest-transport scheduling problem for ease of model calculation as follows:

(1) During the harvesting operation, only one harvester operates in a task unit at any given time.
(2) All agricultural machines (harvesters and grain trucks) depart from the garage and return to the garage after the operation. There is only one warehouse in the same area, and the granary and garage are located in the same place.
(3) The operating parameters of the homogeneous agricultural machines are identical, and no malfunctions occurred during operation. In other words, the operating parameters of all harvesters are the same, and the operating parameters of all grain trucks are the same.
(4) All agricultural machines (harvesters and grain trucks) carry enough fuel to complete the operation tasks, so fuel consumption does not need to be considered.
(5) There are no obstacles within the task units, and all roads are unobstructed. To avoid collisions during transportation, all roads are wide enough to allow for safe vehicle passing.
(6) The location of the warehouse, the location of the fields to be harvested, and the area of the fields awaiting harvest are determined by the regional electronic map.
(7) The quality and yield of the crops to be harvested remain constant within the harvesting period.

4.2. Constructing the electronic farm map

Accurate electronic map information is a prerequisite for operational path planning and agricultural machinery navigation (Li et al., 2021c; Emmi et al., 2021). When performing complete coverage operations of plots, clear field boundary information is needed, and when moving between operational plots, accurate farm road information is required. Therefore, constructing an electronic map becomes crucial.

The electronic map of the farm was constructed using the topological map method. The Zhuozhou farm map data was collected from 20th October to 22nd October 2022. The data collection location was the Zhuozhou Experimental Farm affiliated with China Agricultural University in Hebei. The Qingpu farm map data was collected from 22nd May to 24th May 2024. The data collection location was the Unmanned Eco-Farm in Qingpu District, Shanghai. The collected data included basic details such as farm road information and plot boundary points. The road nodes and plot boundary point coordinates of the farm to be mapped were used to assign numbers to all nodes. Then, the equation for calculating distances under the celestial coordinate system was used to compute the distances between nodes, with the distance values corresponding to the edge weight information, as shown in Eq. (1).

$$
\begin{gathered}
dlat = (lat_2 - lat_1) \times \left(\frac{\pi}{180}\right) \\
dlon = (lon_2 - lon_1) \times \left(\frac{\pi}{180}\right) \\
a = \sin^2\left(\frac{dlat}{2}\right) + \cos\left(lat_1 \times \left(\frac{\pi}{180}\right)\right) \times \cos\left(lat_2 \times \left(\frac{\pi}{180}\right)\right) \times \sin^2\left(\frac{dlon}{2}\right) \\
c = 2 \times \arctan\left(\frac{\sqrt{a}}{\sqrt{1-a}}\right) \\
dist = R \times c
\end{gathered} \tag{1}
$$

where, R is the radius of the Earth, with R being set to 6,378,137 m in this example. *lat1* and *lat2* are the latitudes of the two points, measured in degrees. *lon1* and *lon2* are the longitudes of the two points, measured in degrees. *dlat* is the distance value between two latitude coordinate points, measured in meters. *dlon* is the distance value between two longitude coordinate points, measured in meters. c represents the central angle, and a is an intermediate value used to calculate the central angle c. *dist* is the distance value between the two latitude and longitude coordinate points, measured in meters.

Fig. 2(a) shows the electronic map of the Zhuozhou Farm. Each node represents a road intersection, and each line represents a plot boundary. The topological structure was defined to establish the relationships between different map features. Based on the characteristics of two-way traffic on roads, nodes (points), roads (lines), plots (areas), and their connections were defined, and an adjacency matrix was used to construct the electronic map of the farm. The Zhuozhou Farm was divided into 21 plots, including 16 farmland plots, 4 wasteland plots and one warehouse. Fig. 2(b) shows the remote sensing image of the Zhuozhou Farm.

Fig. 3(a) shows the electronic map of the Qingpu Farm. The Qingpu Farm was divided into 26 plots, including 23 farmland plots, 2

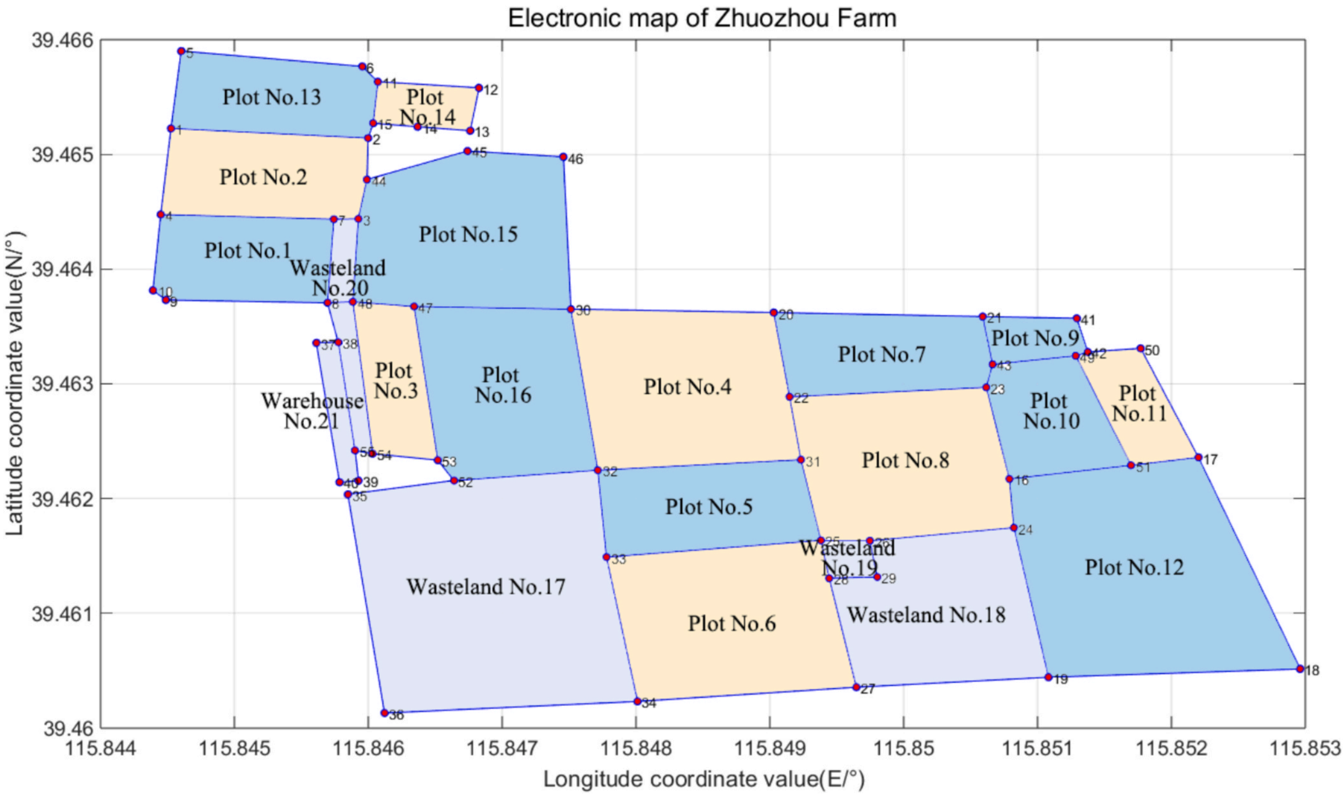

Fig. 2a. Electronic map of the Zhuozhou Experimental Farm.

Fig. 2b. Remote sensing image of the Zhuozhou Experimental Farm.

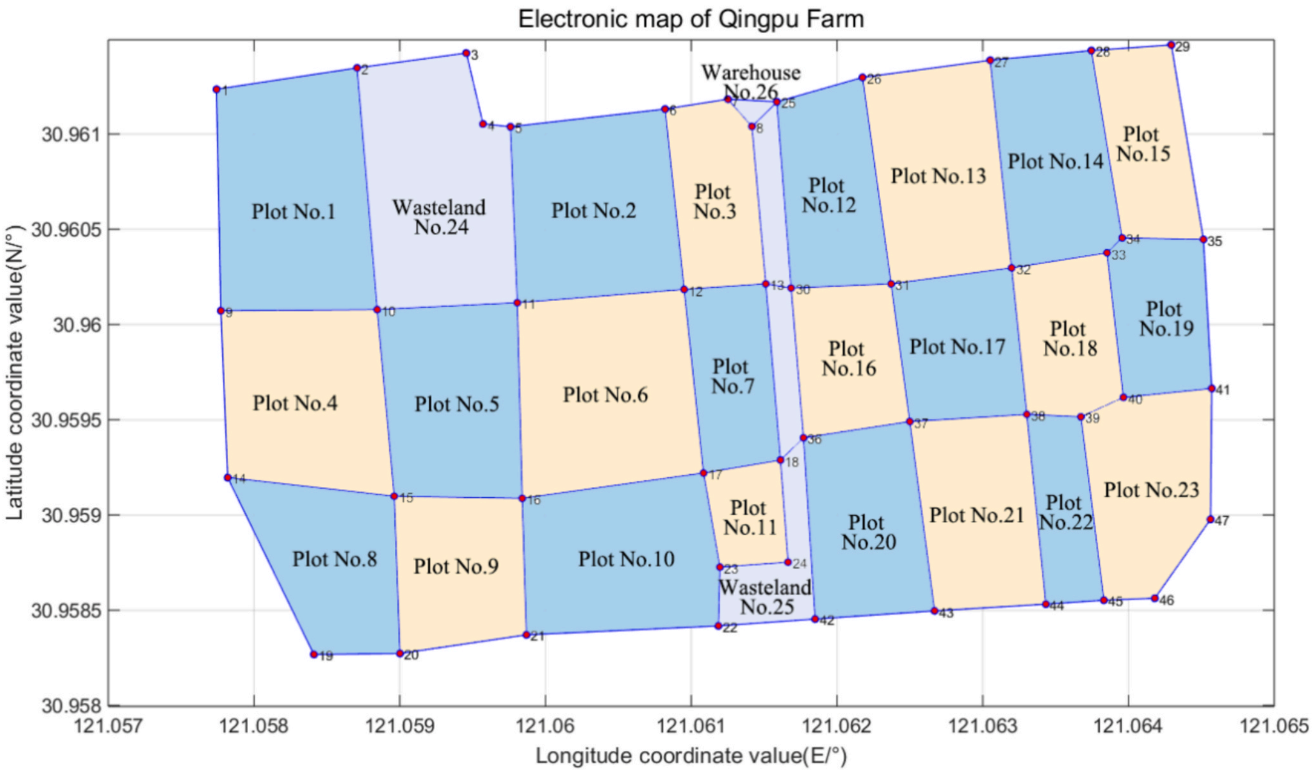

Fig. 3a. Electronic map of the Qingpu Ecological Farm.

Fig. 3b. Remote sensing image of the Qingpu Ecological Farm.

wasteland plots and one warehouse. Fig. 3(b) shows the remote sensing image of the Qingpu Farm.

4.3. Multi-harvester task allocation model

Since the operation of harvesters involves high operational and maintenance costs, a reasonable allocation of harvester tasks is essential (Zhang et al., 2021). Through reasonable allocation of harvester tasks, the operational capacity of the machines can be better utilized, reducing the length of both the operation and transportation paths, avoiding resource waste, and achieving cost savings and efficiency improvements. Based on the constructed electronic map, we plan to establish a harvester task allocation model, solve it using intelligent algorithms, and simultaneously perform path planning after obtaining the harvester task sequence, thereby achieving harvester scheduling.

Based on the problem description, the sets, parameters, and decision variables used in model formulation are defined as follows:

(1) Variable description

The variables related to task plots include the set of task plots $M=\{1,2,3,\ldots,i,\ldots,m\}$, where there are m plots, and i is the plot number. B_i is the entry point of plot i, D_i is the exit point. L_i is the workload of plot i. A_i is the start time for harvesting plot i, and E_i is the end time for harvesting plot i. $F=\{F_1,\ldots, F_i,\ldots,F_m\}$ is the set of boundary points for all task plots.

The variables related to agricultural machinery include the set of harvesters $S=\{1,2,3,\ldots,k,\ldots,s\}$, where there are s harvesters, and k is the harvester number. Sc is the grain tank capacity of the harvester, measured in tons. Sd is the working width, measured in meters. Sh is the harvesting speed, measured in meters per hour. St is the transport speed, measured in meters per hour. Su is the unloading rate, measured in tons per hour.

The task-related variables include the current task sequence assigned to harvesters, task$=\{1,2,3,\ldots,b,\ldots,p\}$, with p tasks in total, where b is the task plot number. $task_k$ is the task sequence assigned to harvester k.

The model uses the following additional parameters. The location of the agricultural machinery garage is Po, which corresponds to note 55 on the Zhuozhou Farm electronic map or note 8 on the Qingpu Farm electronic map. x_{ki} is a binary variable that indicates whether harvester k is assigned to task i. If harvester k is performing task i, then $x_{ki} = 1$, otherwise $x_{ki} = 0$. y^k_{Poi} is a binary variable indicating whether harvester k departs from grain depot Po to perform task i. If harvester k departs from Po to perform task i, then$y^k_{Poi} = 1$, otherwise$y^k_{Poi} = 0$. y^k_{iPo} is a binary variable indicating whether harvester k returns from task i to grain depot Po. If harvester k returns from task i to Po, then$y^k_{iPo} = 1$, otherwise$y^k_{iPo} = 0$.

(2) Objective function

The objective of this model is to minimize the overall operation time T of the harvesters (i.e., to minimize the maximum operation time of all harvesters), including the total harvesting time T_1 within the task plots, the transfer time T_2 from the garage to the first task plot, the total transfer time T_3 from one task plot to the next, and the transfer time T_4 from the last task plot back to the garage.

The harvesting time of the harvester is positively correlated with the workload of the task plot, which refers to the length of the internal harvesting operation path. The total harvesting time of harvester k within the task plots is calculated by:

$$T_{1k} = \sum_{i=1}^{m} \frac{L_i}{S_h} x_{ki} \tag{2}$$

The distance from the garage to the entry point of the first task is obtained using the Dijkstra algorithm. As a result, the transfer time T_2 for harvester k is calculated by:

$$T_{2k} = \sum_{i=1}^{m} \frac{D_{PoBi}}{S_t} y^k_{Poi} \tag{3}$$

The distance from the exit point of the current task to the entry point of the next task is obtained using the Dijkstra algorithm, until the total transfer distance between all task plots is determined. Thus, the transfer time T_3 for harvester k is calculated by:

$$T_{3k} = \sum_{b=1}^{p-1} \frac{D_{DbBb+1}}{S_t} \tag{4}$$

The distance from the exit point of the last task to the garage is obtained using the Dijkstra algorithm, so the transfer time T_4 is calculated by:

$$T_{4k} = \sum_{i=1}^{m} \frac{D_{DiPo}}{S_t} y^k_{iPo} \tag{5}$$

The total transfer and harvesting time for harvester k is calculated by:

$$T_{task_k} = T_{1k} + T_{2k} + T_{3k} + T_{4k} \tag{6}$$

The mathematical model formulated for this problem has the following objective function:

$$f = \min\left(\max\left(T_{task_k}\right)\right) \quad (k \in S) \tag{7}$$

In the above equations, the variables were describes as follows: L_b is the workload of the task plot, in meters. Po is the location of the agricultural machinery garage. Bb is the entry point of the task plot, and Db is the exit point. D_{PoBi} is the transfer distance from Po to the entry point of the first task plot, in meters. D_{DiPo} is the transfer distance from the exit point of the last task plot to Po, in meters. D_{DbBb+1} is the transfer distance from the current task plot's exit point to the next plot's entry point, in meters.

(3) Constraints

Each task plot must be serviced by one harvester exactly once, and multiple harvesters are not allowed to service the same task plot.

$$\sum_{k=1}^{s} x_{ki} = 1 \ \forall i \in \{1, 2, \ldots, m\} \tag{8}$$

Each harvester only leaves the depot once during its operation, which occurs when heading to the first task plot.

$$\sum_{i=1}^{m} y^k_{Poi} = 1 \ \forall k \in \{1, 2, \ldots, s\} \tag{9}$$

Each harvester only returns to the garage once during its operation, which happens after completing the final task plot.

$$\sum_{i=1}^{m} y^k_{iPo} = 1 \forall k \in \{1, 2, \ldots, s\} \tag{10}$$

The harvesting time window of the harvester on task plot i must meet certain conditions.

$$A_i \leq \frac{L_i}{S_h} \leq E_i \tag{11}$$

The time window for the harvester's transition from task plot i to task plot $i+1$ must meet certain conditions.

$$\begin{aligned} A_i &\leq \frac{L_i}{S_h} + \frac{D_{DiBi+1}}{S_t} \leq A_{i+1} \\ E_i &\leq \frac{D_{DiBi+1}}{S_t} + \frac{L_{i+1}}{S_h} \leq E_{i+1} \end{aligned} \tag{12}$$

5. Harvester task allocation and sequence optimization algorithm

The relationship between task allocation and path planning is fundamental to optimizing multi-machine agricultural operations, as these two components are inherently interdependent and essential for achieving operational efficiency. Task allocation involves the reasonable assignment of tasks to machines based on their individual capabilities and the specific requirements of the operation. In contrast, path planning focuses on determining the optimal paths that machines should follow to minimize travel time and overall operational costs. While effective task allocation ensures that tasks are distributed according to the capabilities of each machine, it is path planning that facilitates the efficient execution of these tasks by minimizing delays and preventing route conflicts. However, even well-optimized paths can lead to sub-optimal performance if task allocation is not appropriately managed, as this may result in issues such as machine underutilization or over-burdening, thereby undermining the benefits of path optimization. Therefore, it is essential that both task allocation and path planning are considered in tandem to achieve the overall goals of efficiency and effectiveness in multi-machine agricultural operations, with each process being a necessary prerequisite for the success of the other.

5.1. Task assignment and scheduling using GMM-LB-NNH algorithm

The greedy minimum–maximum load balancing algorithm is a heuristic approach used in optimization problems, especially in task allocation scenarios, where the way tasks are distributed among resources (such as agricultural machinery, processors, or workers) needs to minimize the maximum load between resources. Considering the application scenarios, mathematical models, and constraints, a GMM-LB-NNH algorithm was proposed to address the scheduling problem of multiple agricultural machines in a region.

The proposed GMM-LB-NNH algorithm prioritizes minimizing the maximum load on any resource in each iteration to balance the workload across resources. Additionally, the nearest-neighbor heuristic algorithm is used to optimize the initial allocation results to improve resource utilization or minimize the total workload. A schematic diagram of this method is shown in Fig. 4. First, task parameters, harvester operation parameters, and other data are obtained. Then, the greedy minimum–maximum load balancing algorithm is applied to evenly allocate tasks and generate the harvester task sequence. Afterward, the nearest-neighbor heuristic algorithm is employed to optimize the task sequence, resulting in an optimized sequence. This method can minimize the maximum load across resources in task allocation scenarios while ensuring simplicity, efficiency, and adaptability, making it suitable for various practical applications.

The process of the GMM-LB-NNH algorithm is illustrated in Fig. 5. The specific implementation steps are as follows:

Step 1: Using the constructed multi-harvester task allocation model, build the task plots matrix, the distance matrix between tasks, the distance matrix from the garage to each task, and the distance matrix for returning from each task to the garage.
Step 2: Initialization: Initialize all task sets, task allocation sets, harvester times, and harvester task sequences.
Step 3: Task allocation (greedy minimum–maximum load balancing): For each task, assign it to a harvester, selecting the one that minimizes the maximum potential operation time.
Step 4: Task allocation (greedy minimum–maximum load balancing): Assign the task to the selected harvester, remove the allocated task, adjust the task set, and update the harvester's time and sequence accordingly.
Step 5: Sequence optimization (nearest-neighbor heuristics): For each harvester, apply the nearest-neighbor heuristic to optimize the task order in the harvester's task sequence.
Step 6: Update: Recalculate each harvester's time based on the optimized task sequence and construct the harvester's operation schedule.
Step 7: Output: The task sequence, operation schedule, and the overall operation time of each harvester.

5.2. Whole-process path planning for the harvesters

The harvester's path consists of the complete coverage path within the task plots and the transfer path between task plots (Zhang et al., 2022b). In this paper, to address the whole-process path planning for the harvester, the complete coverage path primarily employed a hybrid path planning method of internal spiral and reciprocating patterns (Wang et al., 2025), while the transfer path mainly used the Dijkstra algorithm based on a topological map.

5.2.1. Complete coverage path planning (CCPP) within the plot

(1) Determination of the entry point of the plot

Using the constructed electronic map of the farm, the Dijkstra algorithm was employed to obtain the shortest distance and the sequence of path nodes between two points. The distance from each boundary point of the plot to the starting point of the longest side was calculated. The boundary point with the smallest distance was then chosen as the entry point of the plot.

(2) Complete coverage path planning (CCPP)

Taking the entry point of the plot as the starting point of the CCPP, the CCPP algorithm (internal spiral + reciprocating method) was used to plan the complete coverage path inside the plot, obtaining the complete coverage path of the plot to be worked on.

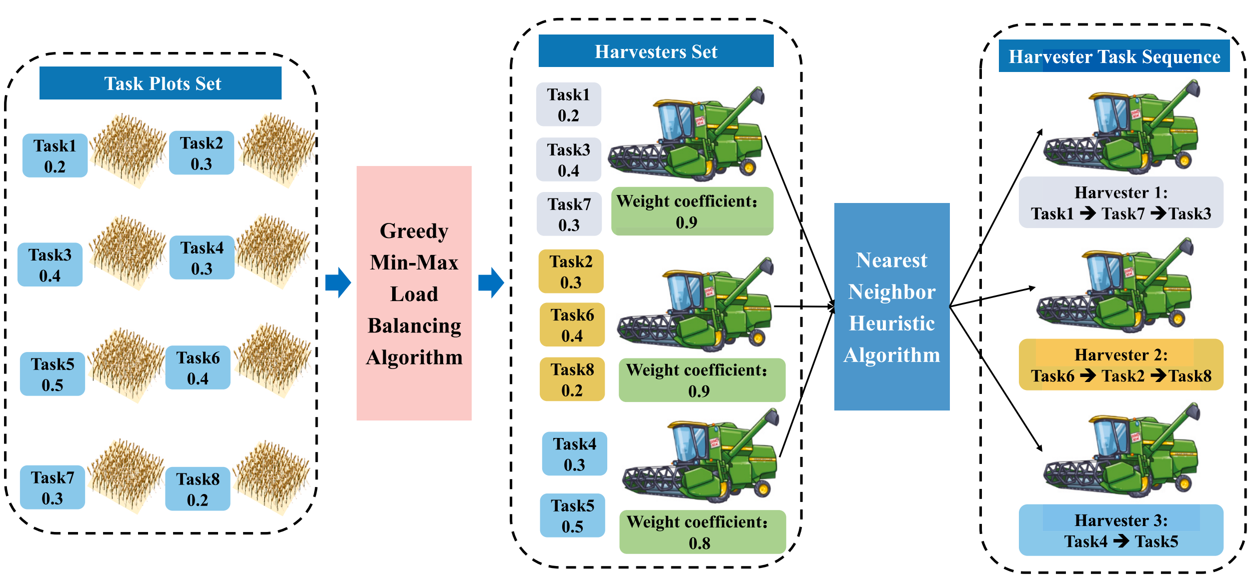

Fig. 4. Schematic diagram of greedy minimum–maximum load balancing algorithm based on nearest-neighbor heuristics (GMM-LB-NNH).

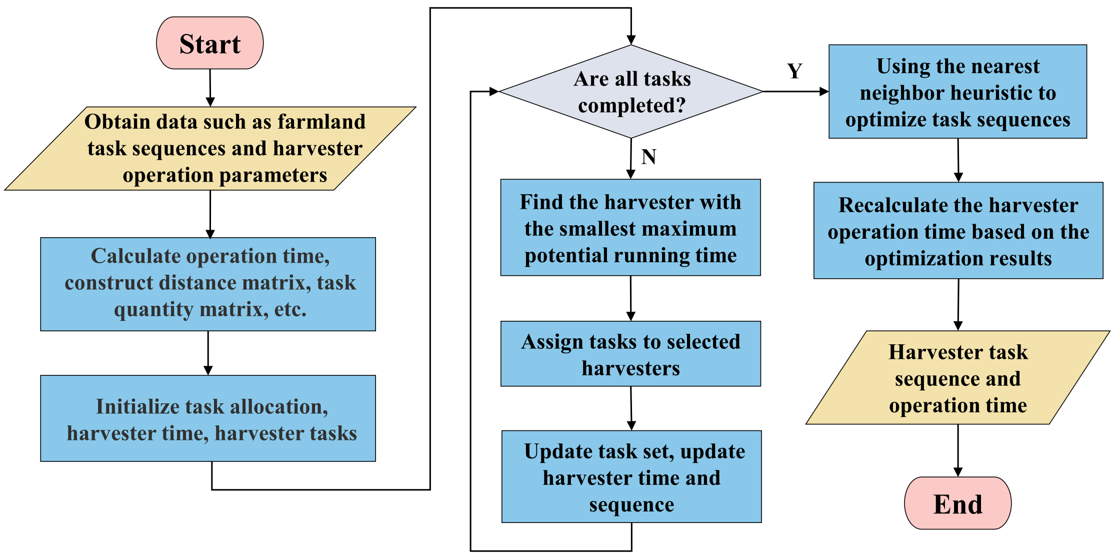

Fig. 5. Flowchart of greedy minimum–maximum load balancing algorithm based on nearest-neighbor heuristics (GMM-LB-NNH).

(3) Determination of the exit point of the plot

Each boundary point of the plot was screened against the endpoint of the complete coverage path, and the boundary point with the smallest distance was selected as the exit point of the plot, recording the entry and exit points for each plot to be worked on.

5.2.2. Transfers path planning between plots

Based on the CCPP, the entry and exit points of the task plots are obtained. According to the task sequence assigned to the harvester, transfer path planning was executed using the Dijkstra algorithm to determine the shortest distance and path node sequence between two points. The transfer path planning is mainly divided into three parts:

Step 1: The harvester travels to the first task plot from the garage. The shortest path was planned between the garage's node number (55 or 8) and the entrance point number of the first assigned task plot, determining the shortest distance and path node sequence.
Step 2: The harvester moved from one task plot to the next. The shortest path was planned between the exit point number of the current plot and the entrance point number of the next task plot, determining the shortest distance and path node sequence.
Step 3: The harvester returned to the garage from the last task plot. The shortest path was planned between the exit point number of the current plot and the garage's node number (55 or 8), determining the shortest distance and path node sequence.

Combining the complete coverage path with the transfer path, the complete operational path of the harvester was determined. The whole-process path planning for multiple harvesters follows the same logic.

6. Simulation results and discussion

The test utilized real farm geographic coordinate data and operational parameters of agricultural machinery. The simulation experiment was conducted on a computer with the Windows 10 operating system, an AMD Ryzen 9-7950X running at 4.50 GHz, AMD Radeon TM Graphics, and 32 GB of RAM. MATLAB R2019b (MathWorks, USA) was employed to execute the simulation.

6.1. Simulation evaluation of task allocation algorithms for multi-harvester systems

6.1.1. Test design

Using the constructed electronic map of Zhuozhou Farm as the simulation scenario, a simulation test was conducted for multi-harvester and multi-plot task allocation. Based on the actual operating parameters of the harvester, the specific simulation parameters are shown in Table 1. Three sets of comparative tests were designed, as shown in Table 2. The experiments randomly selected 5, 10, and 15 task plots in Hebei Zhuozhou Farm to compare the performance of the GMM-LB-NNH algorithm, the Ant Colony Optimization (ACO) algorithm, and the Genetic Algorithm (GA) in the multi-harvester and multi-field task allocation scenarios.

6.1.2. Results and analysis

Under the same parameter settings with different numbers of tasks, the results obtained using the three designed algorithms are shown in Table 3. The number of ants in the ACO algorithm was set to twice the number of tasks, with the influence value of pheromone trails set to one, the influence value of heuristic information set to two, the pheromone evaporation rate set to 0.3, and the number of iterations set to 200. For the GA, the population size was 100, the number of iterations was 200, and the mutation rate was 0.05. The performance of the algorithms was analyzed by comparing the overall operation time and the average running time of the algorithms. The optimal task allocation sequences for the ACO and GA were selected based on the best results from multiple (more than ten) repeated experiments.

The objective of the constructed model is to minimize the overall operation time of the harvesters. As shown in Table 3, regarding overall operation time, the GA only outperforms the proposed GMM-LB-NNH algorithm when the number of tasks is 5, and the task allocation scheme is the optimal result from multiple repeated experiments. In other cases, the proposed algorithm has a shorter overall operation time

Table 1
Basic simulation parameters.

Parameter name	Specific parameters
Number of spiral coverage layers	3 layers
Harvester's working width	3 *m*
Harvester's harvesting speed	3 km/h
Harvester's general travel speed	6 km/h

Table 2
Simulation test plan for task allocation.

Task plots	Task set	Harvester quantity	Task allocation methods
5	[4,8,12,15,16]	2	①GMM-LB-NNH algorithm; ②ACO algorithm; ③GA;
10	[2,4,5,7,8,10,12,13,15,16]	3	
15	[1,2,3,4,5,7,8,9,10,11,12,13,14,15,16]	3	

than the other two algorithms, reducing the average overall operation time by 29.8 min compared to the ACO algorithm and 12.6 min compared to the GA.

In terms of average running time, repeated experiments for each group and each algorithm show that the proposed GMM-LB-NNH algorithm outperforms the other two algorithms, reducing the average running time by 15.0 % compared to the ACO algorithm and 32.1 % compared to the GA.

Under the same parameters, repeated experiments show that the task allocation sequence of the proposed GMM-LB-NNH algorithm is consistent. In contrast, the task allocation sequences of the ACO algorithm and the GA vary each time. This indicates that the proposed algorithm has high stability.

6.2. *Simulation testing of the whole-process path planning for the harvesters*

6.2.1. *Test design*

A total of two experimental groups were designed, with the plans shown in Table 4. Three task plots were randomly selected in Zhuozhou Farm, Hebei, to conduct whole-process path planning for single-machine operations. Eight task plots were randomly selected in Qingpu Farm, Shanghai, with 3 harvesters, to conduct whole-process path planning for multi-machine operations.

6.2.2. *Results and analysis*

The path planning results of Experiment 1, as shown in Fig. 6, display the whole-process path of a single harvester, with the assigned task sequence being 1, 4, and 12.

In Fig. 6, the blue points indicate the entry and exit points of the task plots; the red segments represent the internal spiral path; the green segment represents the reciprocating path; and the yellow segment represents the transfer path. The path is as follows: starting from garage node 55, passing through nodes 38 and 8, and reaching entry point 7 of Plot No. 1 for complete coverage operation. Then, departing from exit point 8 of Plot No. 1, passing through nodes 48, 47, and 30, and reaching entry point 32 of Plot No. 4 for complete coverage operation. Then, departing from exit point 30 of Plot No. 4, passing through nodes 20, 21, 41, 42, 50, and 17, reaching entry point 18 of Plot No. 12 for complete coverage operation. Finally, departing from exit point 19 of Plot No. 12, passing through nodes 27, 28, 25, 31, 32, 52, 53, and 54, returning to garage node 55.

The path planning results of Experiment 2, as shown in Fig. 7, display the whole-process path of the three harvesters. The task sequence for Harvester No. 1 is 1, 11, 14; for Harvester No. 2, 2, 7, 17, 23; and for Harvester No. 3, 4, 10, 21.

In Fig. 7, the inner spiral path and transfer path of Harvester No. 1 are both red, corresponding to Plots No. 1, No. 11, and No. 14. The inner spiral path and transfer path of Harvester No. 2 are both yellow, corresponding to Plots No. 2, No. 7, No. 17, and No. 23. The inner spiral path and transfer path of Harvester No. 3 are both magenta, corresponding to Plots No. 4, No. 10, and No. 21. Due to the overlap of transfer paths, there are instances where the paths of other harvesters are covered. Taking Harvester No. 3 as an example, it starts from garage node 8, passing through nodes 13, 12, 11, 10, and 9 to reach entry point 14 of Plot No. 4 for complete coverage operations. Then, departing from exit point 10 of Plot No. 4, it passes through nodes 15 and 16 to reach entry point 21 of Plot No. 10 for complete coverage operations. Then, departing from exit point 17 of Plot No. 10, it passes through nodes 18 and 36 to reach entry point 37 of Plot No. 21 for complete coverage operations. Finally, departing from exit point 38 of Plot No. 21, it passes

Table 4
Simulation test plan for whole-process path planning.

Task plots	Task set	Harvester quantity	Path planning methods
3	[1,4,12]	1	①Internal spiral and reciprocating method; ②Dijkstra algorithm;
8	[1,2,4,7,10,11,14,17,21,23]	3	

Table 3
Results of algorithm comparison test.

Task plots	Task allocation methods	Optimal task allocation sequence	Operation time (h)	Overall operation time (h)	Average running time of the algorithm (s)
5	①	Task1:4,15,16	6.17	6.17	0.157
		Task2:8,12	5.39		
	②	Task1:8,4,15	6.51	6.51	0.191
		Task2:12,16	5.08		
	③	Task1:8,15,16	6.11	6.11	0.271
		Task2:4,12	5.57		
10	①	Task1:2,15,8	5.60	6.27	0.353
		Task2:4,16,13,10	6.27		
		Task3:5,7,12	5.78		
	②	Task1:2,13,5,16	5.51	6.42	0.394
		Task2:10,7,4,15	6.41		
		Task3:12,8	5.39		
	③	Task1:4,10,15	5.30	6.55	0.494
		Task2:2,8,13,16	6.55		
		Task3:5,7,12	5.78		
15	①	Task1:1,14,16,5,8	6.84	6.91	0.575
		Task2:2,13,15,7,9,10	6.91		
		Task3:3,4,11,12	6.76		
	②	Task1:5,9,7,15	4.93	7.91	0.691
		Task2:14,11,8,4,16,3	7.91		
		Task3:2,13,1,10,12	7.58		
	③	Task1:3,4,5,10,16	7.00	7.00	0.774
		Task2:1,7,9,11,13,14,15	6.88		
		Task3:2,8,12	6.71		

Note: ①refers to the GMM-LB-NNH algorithm.②refers to the ACO algorithm. ③refers to the GA.

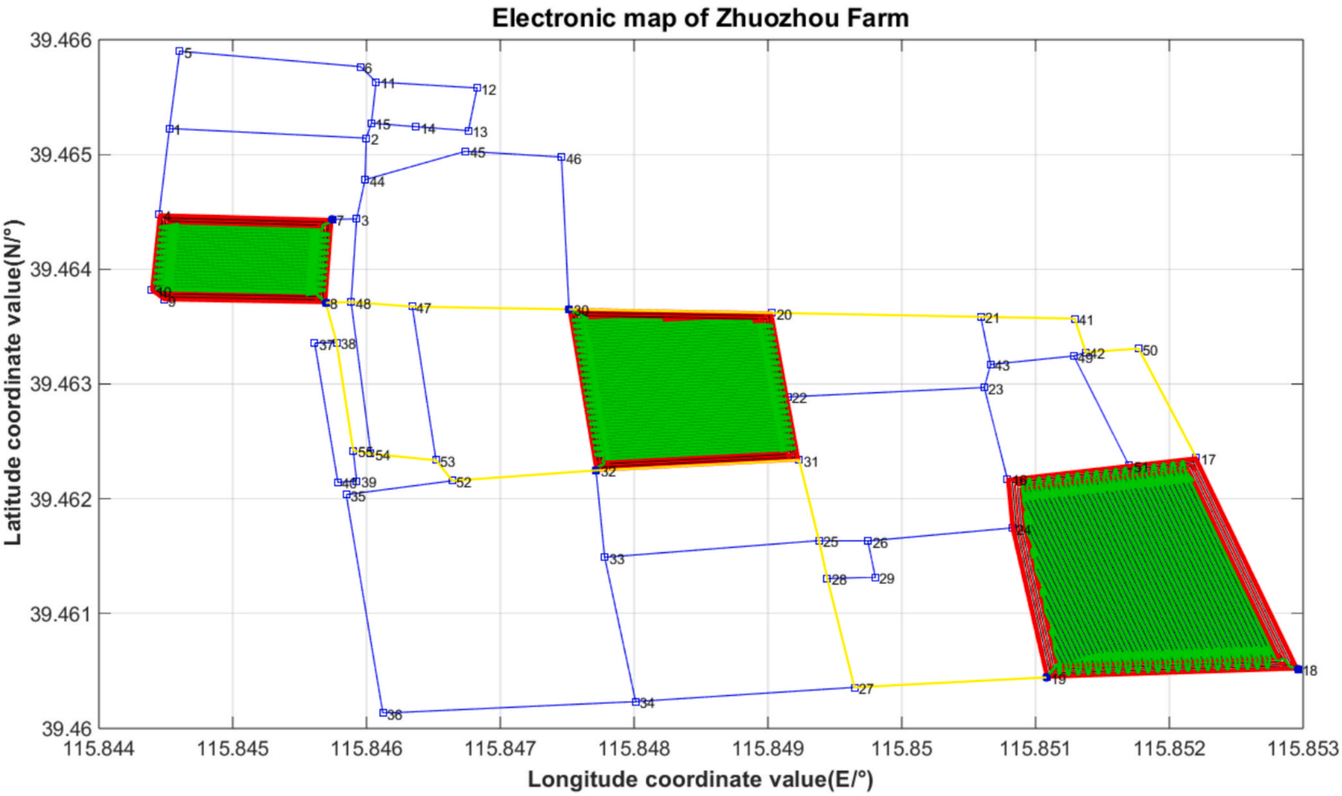

Fig. 6. The whole-process path simulation diagram of a single harvester.

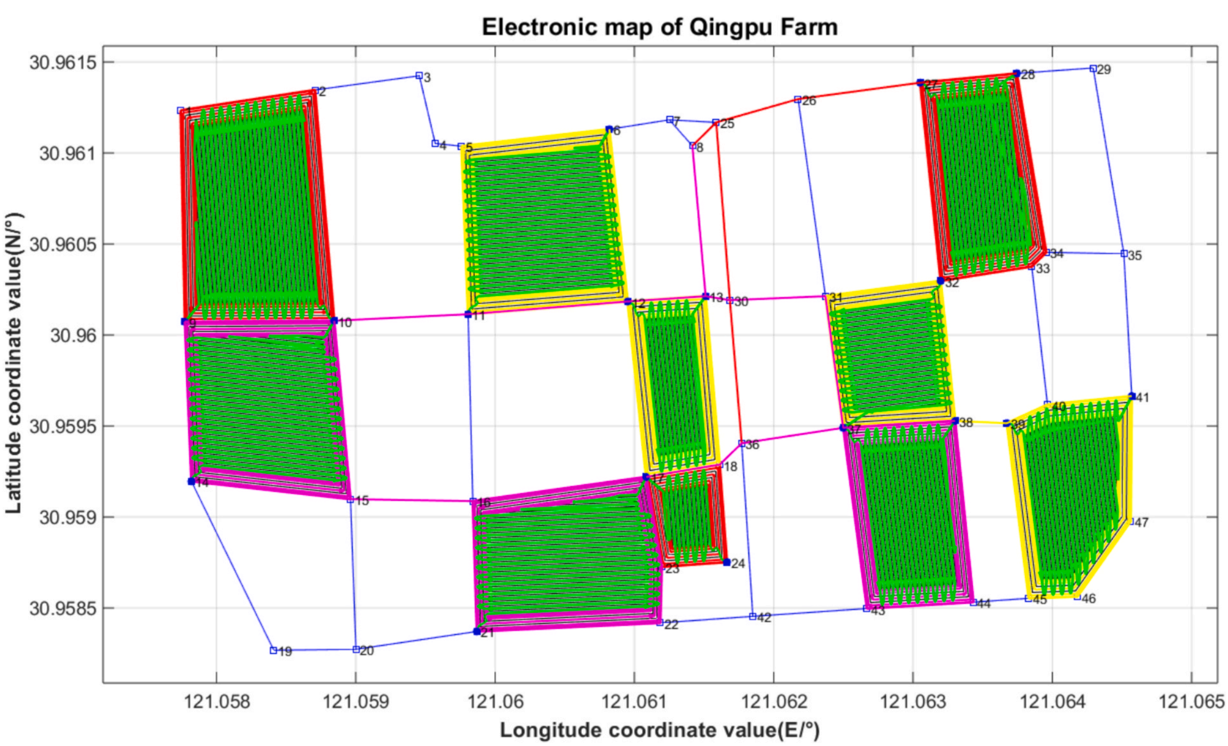

Fig. 7. The whole-process path simulation diagram of the three harvesters.

through nodes 37, 31, 30, and 13, returning to garage node 8.

7. Conclusions

(1) This paper proposed a scheduling method for the task allocation and path planning of harvesters in the harvesting-transportation operation scenario. Based on two established electronic maps of the farm was created, a multi-harvester task allocation model was constructed, while a GMM-LB-NNH algorithm was proposed to solve the model. Finally, the whole-process path planning of the harvester was achieved using complete coverage path and transfer path planning methods.

(2) Using the Zhuozhou Farm electronic map as the simulation scenario, simulation test results for harvester task allocation showed that the proposed GMM-LB-NNH algorithm can allocate tasks to harvesters. The proposed algorithm outperformed the other two algorithms, reducing the average operation time by 29.8 min compared to the ACO algorithm and by 12.6 min compared to the GA. The proposed algorithm demonstrated superior average running time compared to the ACO algorithm and the GA, with a 15.0 % and 32.1 % reduction, respectively. Additionally, the algorithm demonstrated good stability. Using the electronic maps of Zhuozhou Farm in Hebei and Qingpu Farm in Shanghai as simulation scenarios, the complete coverage path and transfer path planning methods were applied for path planning, and the results showed that this method could achieve whole-process path planning for both single and multiple machines.

(3) This research provides a theoretical and technical foundation for the scheduling of harvesters. The proposed method mainly involves scheduling the same kinds of agricultural machinery, such as assigning tasks and planning routes. The study overlooked issues such as in-field obstacles, transfer path conflicts, and fuel consumption of agricultural machinery. Future research should focus on the collaborative scheduling of grain trucks to integrate them effectively with harvesters. Additionally, dynamic factors such as machinery breakdowns and task load variations must be considered to account for the complexity and variability of agricultural environments.

CRediT authorship contribution statement

Ning Wang: Writing – original draft, Methodology, Conceptualization. **Shunda Li:** Validation, Data curation. **Jianxing Xiao:** Investigation, Formal analysis. **Tianhai Wang:** Software, Investigation. **Yuxiao Han:** Resources, Investigation. **Hao Wang:** Project administration. **Man Zhang:** Writing – review & editing, Supervision. **Han Li:** Writing – original draft, Funding acquisition.

Declaration of competing interest

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

Acknowledgements

This work was supported in part by the National Key Research and Development Program of China (Grant No. 2021YFD2000600-2021YFD2000604), China; in part by the 2115 Talent Development Program of China Agricultural University, China.

Data availability

Data will be made available on request.

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