CLOUD-SIDE COLLABORATION-BASED TASK ALLOCATION STRATEGY FOR AGRICULTURAL MACHINE FLEET
/
基于云边协同的农机群任务分配策略

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DOI: https://doi.org/10.35633/inmateh-71-67

Keywords: *cloud robotics, genetic algorithm, farmland tasks, task allocation*

ABSTRACT
In order to rationally plan the amount of tasks and task areas for each agricultural robot in the farm, a cloud-side collaborative task allocation scheme is proposed. The cloud platform divides farm tasks based on field obstacles and extracts the center of gravity prime points for each farm task; plasmas as regional task target points through dynamic genetic algorithms for near-field aggregation, after accelerating the solution process by dynamic crossover and variational operators, the Metropolis criterion is introduced to eliminate the local optimal solution of the algorithm and obtain the globally optimal allocation solution. The simulation experiments demonstrate that the total cost of task execution is reduced by 9.21%, 5.66%, and 7.21% when using four agricultural machines compared to three, five, and six agricultural machines, respectively, and the feasibility of the algorithm is proved experimentally. Reasonable task allocation can improve the overall production efficiency of agriculture, which is informative for unmanned farms operating in large areas.

摘要
为合理规划农场中各个农业机器人任务量与任务区域，提出一种云边协同的任务分配方案。云平台依据田间障碍物划分农田任务，提取各个农田任务重心质点；质点作为区域任务目标点通过动态遗传算法进行近场聚合，经动态交叉、变异算子加速求解过程，引入 Metropolis 准则，剔除算法局部最优解，得到全局最优分配解。仿真实验表明，四台农机执行任务较三台农机、五台农机、六台农机执行任务总代价分别降低了 9.21%、5.66%、7.21%，并通过实验证明了算法的可行性。合理的任务分配，可提高农业整体生产效率，对无人农场大区域作业具有参考价值。

INTRODUCTION
Smart agriculture is the result of fully utilizing modern information technologies, leveraging agricultural data as a production factor, and integrating modern information technologies such as the Internet of Things, big data, and intelligent equipment across agriculture. With the large-scale popularization and application of cloud platform and driverless, the autonomous operation of intelligent farm machinery in unmanned farms has gradually become a mainstream development way (*Huang et al., 2022; Tanzilya. et al., 2021; Jeff, 2020*). Based on Cloud Edge Collaboration technology, according to the difference between the operation site and robot performance, the robots are divided into tasks within the farm, and the operation area is reasonably planned, which helps to utilize the advantages of group operation and improve the operation efficiency (*Nikitenko et al., 2018; Teslya et al 2020; Zhu et al, 2018*).

Cloud-side collaborative work is the process by which the cloud platform divides the area to be worked on and assigns it to a specific robot based on the performance of the swarm of robots within a known environment (*Ferrer et al., 2021*). Task assignment simplifies robotic swarm operations through discrete job scenarios, and is an important research direction for achieving collaborative group operations. At present, the research of cloud-side multi-machine collaboration is mainly in the field of aerospace drones (*Hu et al., 2020*), underwater exploration robots (*Jensen-Nau et al., 2021*), disaster search robots (*Haris et al., 2017*), etc. However, due to the complexity of the agricultural environment and the pressing need to address the issue of full coverage in agricultural machinery operations, there is a lack of research on cloud robot collaboration in

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the field of agriculture. *Xiangyin Zhang et al. (2023*) proposed a two-layer learning search with elite particles to improve the genetic algorithm and reduce the robot search and rescue time. *Fu-Zhen Zhang* and others *(2022)* obtained smoother multi-UAV trajectories on the basis of global cost minimization by establishing heterogeneous target cost matrices to solve the UAV trajectory model separately. *Wang et al., (2023)*, proposed a multi-objective optimization algorithm under multiple constraints with one-inflection point collaboration and introduced the binary crossover method to perturb the local search and verified the effectiveness of the algorithm. *Viraj et al., (2022),* illustrate the key components of a cloud robotics system through an architectural formulation that inspires how cloud robotics systems can be utilized to solve real-world problems. *Rahman et al., (2019)* offloaded multiple tasks to robots individually through a multilevel decision scheme with multilayer genetic algorithms for parcel picking and distribution applications in a 36-cell workspace warehouse scenario with a master robot completing the task flow of assigning 40 nodes. The above studies are mostly on industrial robot collaboration, but have a better guidance for carrying out swarm collaboration on farmland robots.

In this paper, an unmanned farm with smart farm machine collaboration is taken as a research context, where the unmanned farm is partitioned into several sub-areas due to field roads and farm obstacles. A near-field segmentation of the full field is performed by an improved genetic algorithm to obtain several different subsets of tasks to be operated, and the agricultural machines are scheduled to operate in different subsets of tasks in a discrete manner. The operation of different agricultural machines in close proximity to each other reduces the non-operational path loss of significant cross-area operations, reduces operating time, and effectively avoids accidental machine collisions when operating in different subsets of tasks.

MATERIALS AND METHODS

Cloud robotics architecture

Intelligent robots in unmanned farms offload complex issues such as task allocation, job scheduling, and path planning to cloud platforms and edge cloud platforms, and the robots only need to be equipped with basic sensors and basic network equipment to realize farmland operation tasks. As the decision-making layer of intelligent agricultural production, the cloud platform carries out regional segmentation based on the static map provided by the user, forms the operation plan in accordance with the algorithm of the task allocation model, schedules the robots to complete the farm operation tasks, and feeds the monitoring data back to the user in the process of the task execution to ensure the controllability and stability of the operation. The cloud robot architecture is shown in Fig. 1.

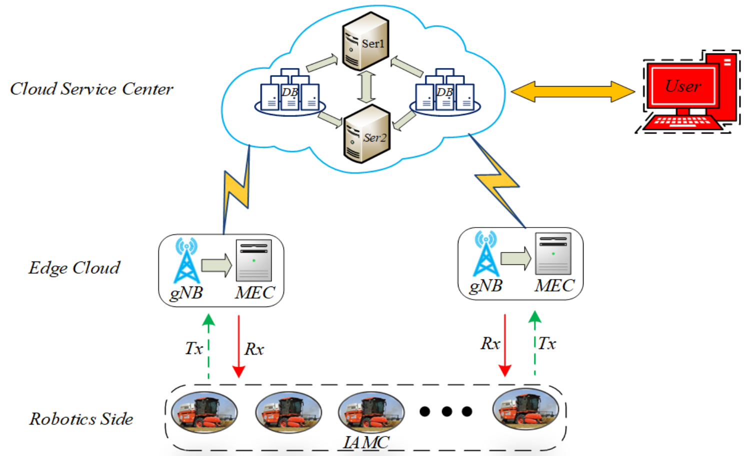


Fig. 1 - Cloud robot architecture

Job scenario analysis

Multi-machine cooperative task assignment is a process of assigning the sequence of operations and tasks to specific farm machines before operations. Take the collaborative harvesting machine scenario in unmanned farm as an example, decompose the irregular farmland geometric model into multiple triangles and calculate the center of gravity, connect the center of gravity to get a simplified graph, continue to solve the center of gravity of the farmland in a loop and use the center of gravity as a task chain traversing the prime points to plan the order of operation of agricultural machines, and the way of planning the center of gravity of the farmland is shown in Fig. 2. The harvester operates round-trip within the sequence of operations at the rated machine operating width, and the farm machinery operates as shown in Fig. 3.

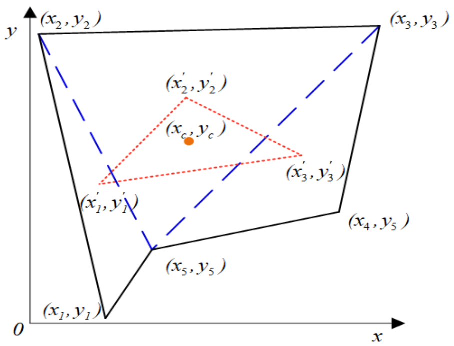


Fig. 2 - Farmland center of gravity planning

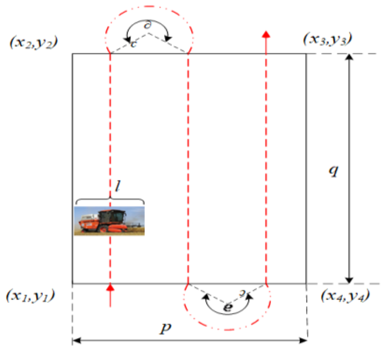


Fig. 3 - Agricultural reciprocating operations

The actual scenarios of group collaboration are complex and variable, in order to simplify the problem and facilitate the planning of mathematical models, the following assumptions are made based on the actual farm scenarios:

(1) The performance parameters and operational parameters of the robot are known; (2) Only one farm machine may operate on each task; (3) The operational path of the farm task is known; (4) Agricultural machines are allowed to duplicate parts of their paths during operations; (5) The mission is considered fully accomplished when all farm machinery returns to the mission rendezvous point.

R: Indicates the group of farm machinery to be assigned to the operation, r is the number of the machine in the fleet, R=$\{1, 2, 3, \ldots, r\}$ and $t > 1$.

T: indicates the total number of current job tasks, t is the assignment number, T=$\{1, 2, 3, \ldots, t\}$ and $t > 1$.

E: denotes the set of performance parameters of the first agricultural machine. $E = \{\upsilon_i, v_i, \omega_i, w_i$ $l_i, c_i, \partial_i, \vartheta_i, \eta_i\}$, υ_i denotes the average speed of the operating state of the agricultural machinery (km/h), v_i denotes the average non-operational speed of the farm machine (km/h), ω_i denotes the power lost in the operating state of the agricultural machine (kW/h), w_i denotes the non-operational power loss of the farm machine (KW/h), l_i denotes the width of the agricultural machinery (m), c_i denotes the turning radius of farm machinery (m), ∂_i denotes the turning angle of the farm machine, ϑ_i denotes the operational efficiency of agricultural machinery (m^2/h), η_i denotes the residual energy of the farm machinery (kW).

M: denotes the set of task parameters **M**=$\{a_t, (x_{1t}, y_{1t})(x_{2t}, y_{2t})(x_{3t}, y_{3t})(x_{4t}, y_{4t})(x_{ct}, y_{ct}), p, q, d\}$, a_t denotes the size of the task area (m^2), , $(x_{1t}, y_{1t})(x_{2t}, y_{2t})(x_{3t}, y_{3t})(x_{4t}, y_{4t})$ denotes the coordinates of the execution point of the task operation, p denotes the maximum horizontal width of the farmland (m), q denotes the maximum vertical length of the farmland (m), d denotes the distance between the centers of gravity of neighboring subregions (km).

Multitasking job cost function

According to Job Scenario Analysis, the task cost is generated during the operation of the agricultural machine, which is mainly composed of the total path traveled, the maximum task completion time and the total energy loss. Assuming that there are r agricultural machines, t operational tasks available in the environment, the following objective function can be defined:

$$f = \lambda \max(S_i) + \mu \sum_{i=1}^{r} L_i + \delta \sum_{i=1}^{r} Q_i + f_p \tag{1}$$

In the formula, f is the operational generation value, S_i is the total amount of time it takes for the farm machine to complete its task, L_i is the total path of agricultural machinery to accomplish a task, Q_i is the total energy loss of the farm machine to accomplish the task, λ, μ, δ is the weighting factor and $\lambda, \mu, \delta \in [0,1]$, f_p is the penalty function in the task system.

Task assembly point $\Upsilon = (x_s, y_s)$ as point 0, the t subregions are the 1st to the points in order, therefore, the center of gravity distance matrix d between any two subregions in the farm is:

$$d=\begin{bmatrix} d_{00} & \cdots & \cdots & d_{0t} \\ \vdots & 0 & & d_{ji} \\ d_{ij} & & 0 & \vdots \\ d_{t0} & \cdots & \cdots & d_{tt} \end{bmatrix} \tag{2}$$

On the basis of the complete workload T, task subset partitioning of farmland based on operation-independent factors such as farm roads and non-operational farmland yields a set of neighboring aggregated tasks U_τ for continuous operations. Within the operation subset U_τ, the tasks are performed by the designated farm machine E_r^τ. The mathematical model is given in the following equation:

$$T = U_1 + U_2 + \ldots + U_\tau \tag{3}$$

$$U_\tau = M_i + \ldots + M_j \qquad i, j \in \{1, 2, \cdots t\} \tag{4}$$

$$\mathrm{E}_r^\tau \to U_\tau \tag{5}$$

The time S_i for a farm machine to complete a task consists of three parts: the time for the regional transition, the time for the task operation, and the time for the return trip, and the task time is calculated by the formula:

$$S_i = \sum_{t=1}^{\lceil U_\tau \rceil} \frac{d_{t-t+1}}{v} + \sum_{t=1}^{\lceil U_\tau \rceil} \left(\left\lceil \frac{p}{l} \right\rceil \frac{q}{\upsilon} + \frac{\partial c}{\upsilon} \left\lfloor \frac{p}{l} \right\rfloor \right) + \frac{d_{t-\Upsilon}}{v} \tag{6}$$

The distance L_i of the path of the farm machine to complete the task consists of three parts: the regional path transformation, the path of the farm machine operation, and the return path of the farm machine, and the total path of the task is calculated by the formula:

$$L_i = \sum_{i=1}^{r} \sum_{i=1}^{\lceil U_\tau \rceil} d_{i,i+1} + \sum_{i=1}^{r} \sum_{i=1}^{\lceil U_\tau \rceil} \left(\left\lceil \frac{p}{l} \right\rceil q + \partial c \left\lfloor \frac{p}{l} \right\rfloor \right) + \sum_{i=1}^{r} d_{k-\Upsilon} \tag{7}$$

The energy loss Q_i of the farm machine to complete the task consists of three parts: the energy loss of the farm machine adjacent to the task shift, the energy loss of the farm machine operation, and the energy loss of the farm machine return trip, and the energy loss is calculated by the formula:

$$Q_i = \sum_{i=1}^{\lceil U_t \rceil} \frac{d_{i-i+1}}{v} w_i + \sum_{t=1}^{\lceil U_\tau \rceil} \left(\left\lceil \frac{p}{l} \right\rceil \frac{q}{\upsilon} + \frac{\partial c}{\upsilon} \left\lfloor \frac{p}{l} \right\rfloor \right) \omega_i + \frac{d_{t-\Upsilon}}{v} w_i \tag{8}$$

After the initial task allocation scheme is formed, the feasibility of this scheme is evaluated by substituting the average operating efficiency of the agricultural machine as a parameter into the penalty function. The penalty function f_p is given in the following equation:

$$f_p = \sum_{i=1}^{t} a_i - \frac{\sum_{i=1}^{r} S_i}{r} \vartheta + \zeta \left(\frac{\sum_{i=1}^{t} a_i}{\vartheta r} - \frac{\sum_{i=1}^{r} S_i}{r} \right) \tag{9}$$

In the formula, the area of operation is predicted with the average operating time and operating efficiency of all agricultural machines of the program, and compared with the total area of the actual task. Second, depending on the complexity of the operating environment, the total working time in the ideal state is calculated and differed from the actual working time as a measure of the cost factor of energy consumption, and the parameter ζ is calculated as follows:

$$\zeta = \begin{cases} 1 & Q_i < \eta_i \\ \infty & Q_i \geq \eta_i \end{cases} \tag{10}$$

Genetic code

Traditional genetic algorithms have strong stochastic search ability and global optimization ability, but the random crossover and mutation methods are prone to premature emergence of local optimal solutions, which cause the algorithm to converge prematurely (*Alan et al., 2021; Wang et al., 2021*).

In order to ensure that the algorithm can find the optimal solution, the dynamically adjusted crossover operator and variation operator are designed; and the Metropolis criterion is introduced to enhance the ability of the algorithm to jump out of the local optimal solution.

The chromosome is encoded in three distributed segments, with the first segment representing the sequence of tasks, t tasks grouped in chaotic order from 1 to t, with a total of t positions. The second paragraph indicates the number of operating farm machinery, with 1 digit. The third segment indicates the number of the farm machine, corresponding to the intermittent tasks, respectively, with a total of r digits. Chromosomal gene coding is shown in Fig. 4.

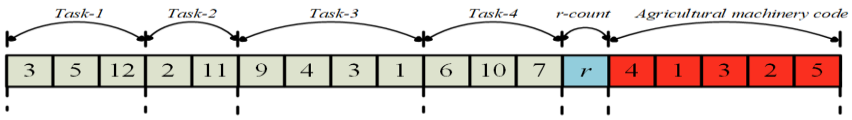


Fig. 4 - Chromosome gene coding map

Choice of operator

In this paper, roulette algorithm with elite retention strategy was chosen to design the selection operator. According to the encoding design in Figure 4, an initial population of C individuals is generated. By calculating the fitness of each individual using Formula 1, the fitness value of individual i in the population is obtained as f_{Ci}. Using the optimal value f_{max} of the population from each iteration as the evaluation criteria, $C1$ elite individuals are selected. Subsequently, the complementary population $C2$ is obtained by dynamically updating the crossover operator with the variation operator, and the population update process is as follows:

$$p_i = \frac{f_{Ci}}{f_{max}} \tag{11}$$

$$C1 = \left\lceil \frac{\sum_{i=1}^{C} f_{Ci}}{f_{max}} \right\rceil \tag{12}$$

$$C = C1 + C2 \tag{13}$$

Dynamic crossover, Variational operators

Gene crossover is the recombination of slices of genes at different locations on a chromosome, and gene mutation is the mutation of a gene at a random location on a chromosome. In order to accelerate the process of population evolution, the crossover probability P_C and mutation probability P_m are dynamically adjusted according to the relationship between the difference between the current individual fitness value of the population and the average fitness value of the population, as well as the elite retention of the population $C1$. The dynamic calculation formula is as follows:

$$P_c = \begin{cases} k_1 \cos[(\frac{f_{max} - f^{'}}{f_{max} - \overline{f}})\frac{C - C1}{C}] & f^{'} \geq \overline{f} \\ k_2 & f^{'} < \overline{f} \end{cases} \tag{14}$$

$$P_m = \begin{cases} k_3 \cos[(\frac{f_{max} - f^{'}}{f_{max} - \overline{f}})\frac{C - C1}{C}] & f^{'} \geq \overline{f} \\ k_4 & f^{'} < \overline{f} \end{cases} \tag{15}$$

In the formula, f_{max} is the maximum value of current population fitness, $\overline{f}$ is the mean value of population fitness, $f^{'}$ is the value of cross individual fitness, k_1, k_2 is the crossover coefficient, k_2 is the default coefficient of the crossover operator and $k_1 + k_2 = 1.0$, k_4 is the default coefficient of the variation operator and $k_3 + k_4 = 1.0$.

Improved genetic algorithm flowchart

Dynamic crossover, variational operators improve the ability to find local optima, but the algorithm is prone to terminate early and ignore the global optimum. Therefore, it is necessary to expand the search scope to jump out of the local optimal solution. The Metropolis criterion accepts floating solutions with a certain probability, which strengthens the fault tolerance of the algorithm and enables it to probabilistically jump out of the local optimal solution.

The probability p_s mathematical model is as follows:

$$p_s = \begin{cases} e^{-\frac{|f_{Ci}-\overline{f}|}{mx-0.95mf}} & 0.8\overline{f} \le f_{Ci} \le 1.2\overline{f} \\ 1 & f_{Ci} < 0.8\overline{f},\ f_{Ci} > 1.2\overline{f} \end{cases} \tag{11}$$

In the formula, mx is the maximum number of iterations of the algorithm, mf is the number of iterations of the current algorithm. The flow of the improved genetic algorithm is shown in Fig. 5.

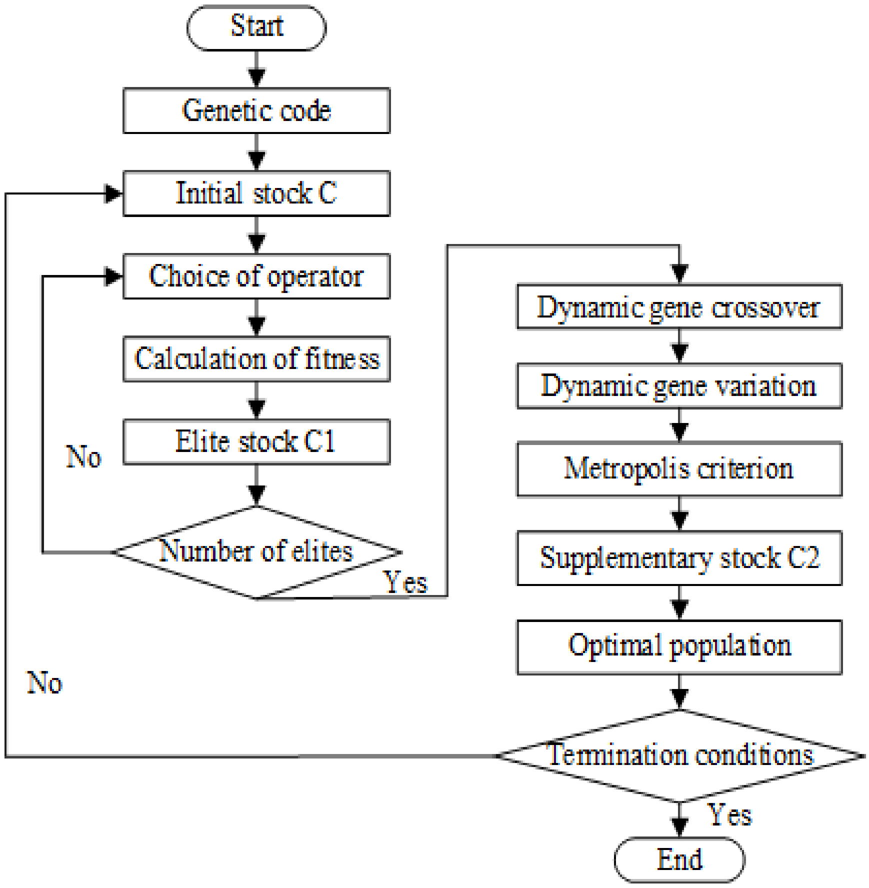
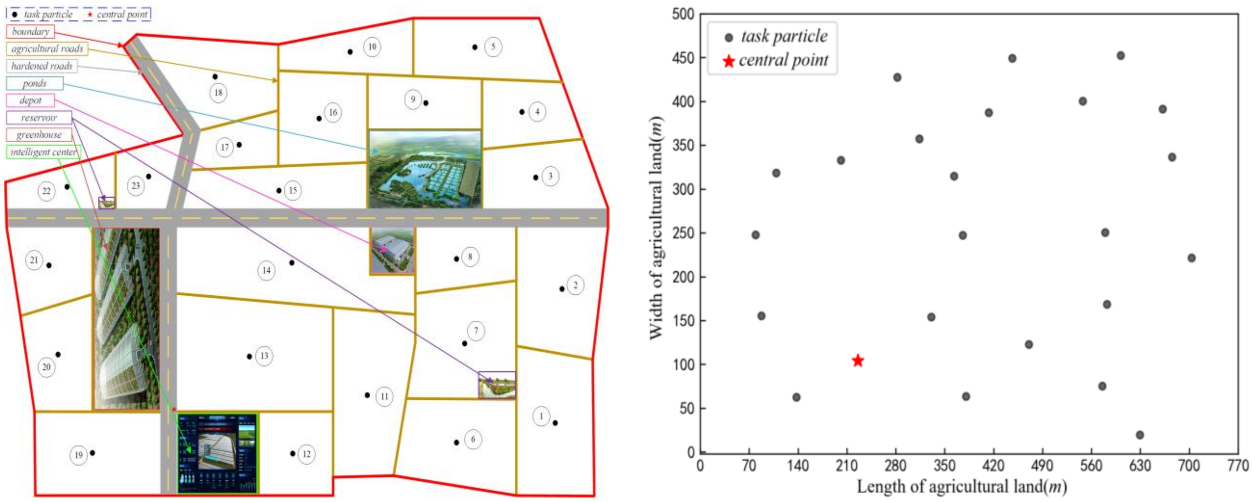


Fig. 5 - Improved genetic algorithm flowchart

RESULTS

Task preprocessing

In order to verify the feasibility and effectiveness of the allocation algorithm in this paper, simulation experiments are carried out in Windows 10 system based on python3.9 environment. Taking the unmanned farm as the experimental environment, after extracting the unmanned farm e-map, the unmanned farm is divided into multiple sub-regions based on multiple field obstacles, and the center of gravity of each sub-region is extracted as the task chain traversal prime point, and the farm e-map is shown in Fig. 6(a). The electronic map of the farm is converted into map feature information that can be recognized and stored by the computer, and the length and width of the farmland are used as the horizontal and vertical axes within the two-dimensional coordinate system to establish the farm task mass map, as shown in Fig. 6(b).



a) Map of the farm *b) Map of the center of gravity of farmland*

Fig. 6 - Farm map

Subset division of agricultural machinery tasks

The task chain formed by the elite ant colony algorithm is used as the basis for subset division. The partial parameters of the task plot obtained according to the task platform in the experiment are shown in Table 1, and the partial parameters of the performance of the six agricultural machines are shown in Table 2.

Table1

Parameters of the mission plots

Farmland serial number	Area (m^2)	Coordinate of the mass point	Farmland serial number	Area (m^2)	Coordinate of the mass point
1	16390.54	(698.4,96.4)	13	20707.13	(330.7,154.2)
2	16515.65	(703.2,221.7)	14	24085.33	(375.7,247.3)
3	14451.20	(675.1,336.4)	15	15577.27	(363.1,314.7)
4	12386.74	(661.7,391.4)	16	13387.69	(412.7,387.3)
5	14200.96	(601.8,452.3)	17	10947.88	(313.4,357.4)
6	16202.86	(575.4,75.2)	18	17078.69	(282.1,427.3)
7	16953.57	(582.3,168.7)	19	15452.15	(137.4,62.7)
8	11510.91	(579.7,250.3)	20	13575.37	(87.4,155.4)
9	11198.11	(547.6,400.2)	21	10572.52	(79.3,247.8)
10	13325.13	(446.7,449.1)	22	10760.20	(108.7,318.6)
11	17579.16	(470.4,122.8)	23	8695.74	(201.4,332.7)
12	11948.83	(380.4,63.4)			

Table 2

Performance parameters of agricultural machines

Farmland serial number	Operating rate (km/h)	Non-operating rate (km/h)	Operating loss (kW/h)	Non-operating loss (kW/h)	Average efficiency (m^2/h)	Energy (kJ)
1	4.60	9.7	57.81	29.78	6500	4617.324
2	4.50	10.2	60.13	29.41	5300	4958.424
3	4.30	9.6	57.61	28.97	5600	4849.956
4	4.10	9.7	59.12	29.45	6000	5063.112
5	3.90	9.8	58.21	30.51	6200	5009.292
6	4.60	10.1	59.34	28.98	5800	5356.224

Assuming that the operating state of the farm machine is exactly the same as the planning operating state of the algorithm, the initial population size of the improved genetic algorithm is 30, and the initial p_c=0.6, p_m=0.2, k_1=0.4, k_2=0.6, k_3=0.8, k_1=0.2. After 1000 iterations, the optimal solution for task assignment of different groups of agricultural machines is obtained, and the task operation flow is shown in Figs. 7 to 10.

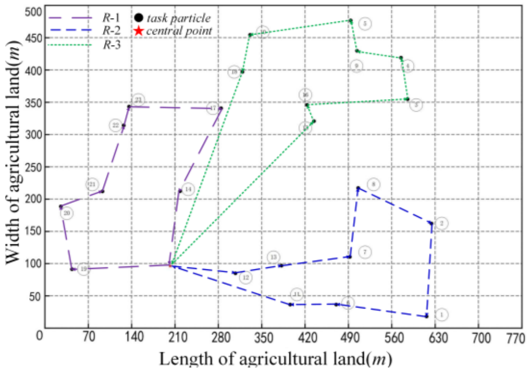


Fig. 7 - Three farm machines in operation

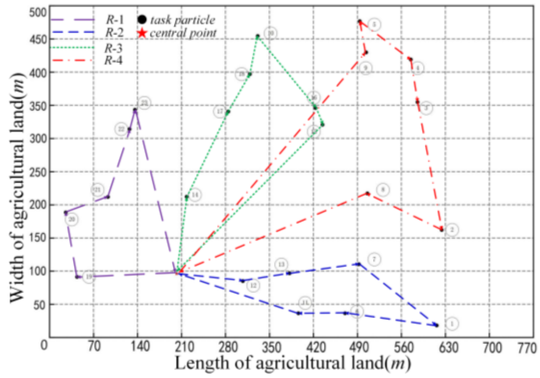


Fig. 8 - Four farm machines in operation

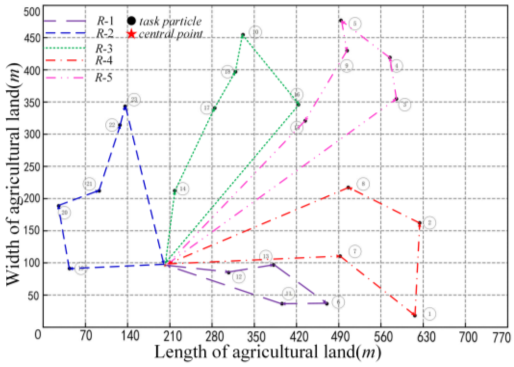


Fig. 9 - Five farm machines in operation

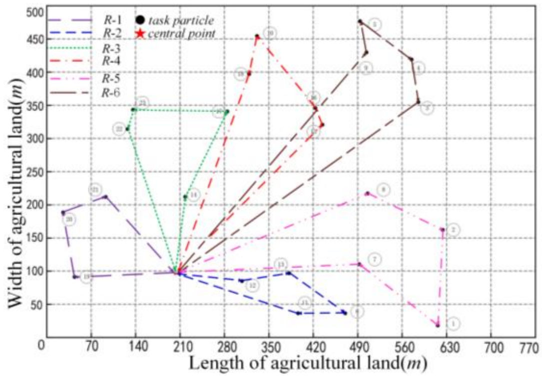


Fig. 10 - Six farm machines in operation

The unmanned farm is divided into 23 farmland tasks to be operated, and the improved genetic algorithm is used to plan the task area for farm machinery operation, and output the chromosome solution for task allocation, which is decoded to obtain the different farm machinery task sequences, and the farm machinery task sequences are shown in Table 3. In the allocation scheme, the task cost is analyzed by the task sequence of the agricultural machine and the performance parameters of the agricultural machine, and the maximum operating time of the agricultural machine, the total loss of task energy, the total path of the task and the penalty function are taken as the initial evaluation criteria, and the secondary evaluation is carried out based on the differences in the weighting ratio of the four and is taken as the total cost of the task, and the final task cost of the operation is shown in Table 4.

Table 3

Sequence of agricultural machinery tasks

Number of agricultural machines	Task ① Sequence	Task ② Sequence	Task ③ Sequence	Task ④ Sequence	Task ⑤ Sequence	Task ⑥Sequence
three	19→20→21→22 →23→17→14	12→13→7→8 →2→1→6→11	15→16→3→4→ 9→5→10→18			
four	19→20→21→22 →23	12→13→7→ 1→6→11	14→17→18→10 →16→15	9→5→4→3 →2→8		
five	12→13→6→ 11	19→20→21→ 22→23	14→17→18→10 →16	7→1→2→8	3→4→5→9 →15	
six	19→20→21	12→13→ 6→11	14→17→23→22	15→16→10 →18	8→2→1→7	9→5→4→3

Table 4

Cost of agricultural machinery tasks

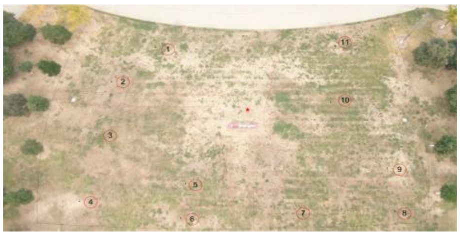
Number of agricultural machines	Maximum operating time (h)	Energy loss (kJ)	Total path (km)	Non-operational path (km)	Penalty function	Aggregate consideration
three	18.98	11065.104	226.71	3.77	41.73	1171.39
four	14.82	10799.388	227.32	4.38	25.16	1127.23
five	12.25	10598.292	227.93	4.99	-18.04	1063.45
six	10.52	10927.62	228.45	5.51	33.27	1146.10

According to Table 4, the maximum operating time of the six farm machines is the smallest, and this option should be preferred when faced with tasks that are more agro-temporal. However, the operation of multiple farm machines causes an increase in the non-operational path and penalty function thereby increasing the total cost, and the penalty function in the table shows peaks and valleys with the increase in the number of farm machines. In this task allocation five farm machines were the most reasonable, the total cost of the task was reduced by 7.21% compared to six farm machines, but the operating time was increased by 16.44%, which was difficult to meet the requirements in the face of the task with strong agronomic nature. It can be seen that when faced with different agricultural tasks should be based on different operational needs to determine a reasonable allocation program to ensure the optimal global benefits.

Experimental verification

In the actual operation of the unmanned farm, the information collection robot can collect the growth conditions of crops at different growth stages in the farmland by traversing the farmland with the RMONCAM HD600 infrared camera. In this paper, the task assignment and field full traversal experiments were conducted by the farmland information collection robot built by Shandong University of Science and Technology in cooperation with Zibo Harvest Seed Industry Company, the experimental site was the south lawn of the library of Shandong University of Technology.

This paper collects the map of the experimental environment and transforms it into an electronic map to provide a basis for subsequent task allocation, simulates the actual agricultural production activities to divide the experimental site into 11 sub-areas, as shown in Fig. 11, and selects three information acquisition robots to carry out experimental verification. Some of the operational parameters of the three information-gathering robots are summarized in table 5.



a. Task segmentation

b. Robot field traversal

Fig. 11 - Farm task operation

Table 5

Operational parameters of the information-gathering robot

Number of agricultural machines	Operating rate (m/s)	Non-operating rate (m/s)	Turning radius (m)	Operating width (m)
r-1	1.4	2.1	1.5	1.2
r-2	1.4	2.1	1.5	1.2
r-3	1.8	2.7	1.8	1.5

In this experiment, the sequence of tasks for each robot is r-1:4→3→2→1,r-2:5→6→7,r-3:8→9→10→11.The robot departs from the mission rendezvous point (the pentagonal labeled point in Fig. 11a), sequentially into the planning work area, and return to the mission rendezvous point upon completion of all tasks. The cloud platform counts the actual traversed area, area repetition rate, and the actual working time of each robot to complete the task, and monitors the execution of the whole task, designing the human-machine interaction interface as in Fig. 12, and the results of the operation data statistics are shown in Table 6.

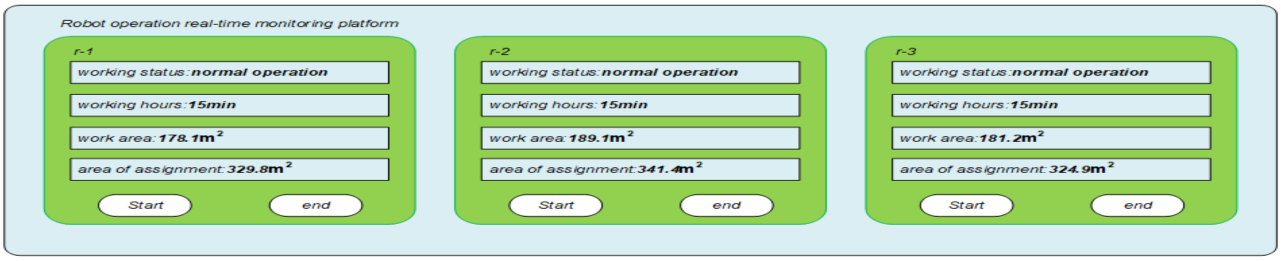


Fig. 12 - Human-machine interaction interface

Table 6

Machine operation data

Cloud data	r-1	r-2	r-3
operating area (m^2)	376.5	414.4	385.7
area repeatability	14.15%	21.4%	18.7%
operation time (min)	34.7	42.1	38.7

In this paper, the task allocation is based on the theoretical workload of each robot, and the farm operation is planned in a theoretically optimal way, so the path repetition rate is low when each robot traverses. As can be seen from Table 7, each of the participating robots is able to achieve 100% coverage of their respective work areas, and all of them are able to complete the traversal task within a short working time, which proves the effectiveness of the proposed algorithm.

CONCLUSIONS

The large-scale operation of unmanned farms is the direction for the development of smart agriculture. Compared to traditional manual labor, the operational capacity of unmanned agricultural machinery far exceeds the former. Based on the information of different agricultural lands and the performance parameters of agricultural machinery, this paper establishes an objective function to reasonably allocate tasks, ensuring the optimal use of resources. This has reference value for the large-scale operation of unmanned farms.

This paper establishes a multi-machine task cost model and maps the operation time, energy loss, and task path into the improved genetic algorithm. It analyzes task allocation schemes for different numbers of agricultural machinery to achieve optimal collaborative benefits among multiple machines. The results indicate that the optimal task allocation scheme is to deploy five agricultural machines, which reduces energy loss by 4.22%, 1.86%, and 3.01% respectively compared to operations with three, four, and six machines. Additionally, it lowers the total cost by 9.21%, 5.66%, and 7.21% in each scenario. The on-site operations demonstrate that the algorithm is capable of completing the assigned tasks with relatively low task costs.

ACKNOWLEDGEMENT

This work was funded by the Top Talents Program for One Case One Discussion of Shandong Province, the Key Research and Development Program of Shandong Province (Major Innovative Project in Science and Technology) (2020CXGC010804), Shandong Provincial Natural Science Foundation (ZR2021MC026).

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