SIMULATED ANNEALING GENETIC ALGORITHM-BASED HARVESTER OPERATION SCHEDULING MODEL

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基于模拟退火遗传算法的收割机作业调度模型

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ABSTRACT
To address problems involving the poor matching ability of supply and demand information and outdated scheduling methods in agricultural machinery operation service, in this study, we proposed a harvester operation scheduling model and algorithm for an order-oriented multi-machine collaborative operation within a region. First, we analysed the order-oriented multi-machine collaborative operation within the region and the characteristics of agricultural machinery operation scheduling, examined the revenue of a mechanized harvesting operation and the components of each cost, and constructed a harvester operation scheduling model with the operation income as the optimization goal. Second, we proposed a simulated annealing genetic algorithm-based harvester operation scheduling algorithm and analysed the validity and stability of the algorithm through experimental simulations. The results showed that the proposed harvester operation scheduling model effectively integrated the operating cost, transfer cost, waiting time cost, and operation delay cost of the harvester, and the accuracy of the harvester operation scheduling model was improved; the harvester operation scheduling algorithm based on simulated annealing genetic algorithm (SAGA) was able to obtain a global near-optimal solution of high quality and stability with high computational efficiency.

摘要
针对农机作业服务供需信息匹配能力弱、调度方式落后的问题，该文针对区域内面向订单的多农机协同作业模式，建立了收割机调度模型及算法。首先对区域内面向订单的多农机协同作业模式进行了明确，并建立了以机收作业总收益为优化目标的收割机作业调度模型；其次，设计了基于模拟退火遗传算法的收割机作业调度算法，并通过相关仿真实验对算法的有效性、稳定性及计算效率进行了分析。研究结果表明：建立的收割机作业调度模型有效整合了使用成本、转移成本、等待时间成本、延误作业损失成本信息，提高了收割机作业调度模型的准确性；基于模拟退火遗传算法的收割机作业调度算法可以获得质量较高的全局近优解，具有较高的计算效率。

INTRODUCTION
With the improvement of agricultural machinery social service systems, agricultural machinery social services are becoming increasingly popular in rural China *(Dong and Li, 2015)*. Faced with the expanding scope of agricultural machinery services and the informationisation needs of agricultural machinery operations, traditional scheduling management techniques such as manual scheduling and telephone scheduling can no longer meet the needs of social services at this stage. Problems such as the poor matching efficiency of supply and demand information for agricultural machinery services and untimely updates of operation information can waste agricultural machinery resources or delay agricultural production *(Wu et al., 2013; Zhou et al., 2014)*. Establishing an agricultural machinery operation scheduling model, suitable for the collaborative operation of agricultural machinery entities, is the key to realizing agricultural machinery scheduling information management and is of great significance for improving agricultural machinery use efficiency and benefits *(Luo and Zhang, 2016; Zhang, 2020)*.

Agricultural machinery operation scheduling and planning have been extensively investigated, and typical operational research formulations for industrial manufacturing and logistics transportation have been applied in this area *(Bochtis et al., 2014)*. By drawing from ideas for vehicle scheduling, *Guan et al. (2018)* proposed a two-stage metaheuristic algorithm for mechanized harvesting on sugarcane farms, in which the initial job scheduling scheme was generated based on the priority rules and then optimized using a genetic algorithm. *He et al. (2018)* constructed a scheduling model with the total operation time as the optimization goal and the operation time of each harvester as a constraint while considering the effects of different machine models and soil types on scheduling. *Thuankaewsing et al. (2015)* proposed a sugarcane harvester operation scheduling model with the highest yield as the optimization goal and the proportion to which each sugarcane field is harvested at the time of the highest yield as a constraint. *Edwards et al. (2015)* proposed an agricultural machinery scheduling model that considered farmland operating conditions and solved it with an improved tabu search algorithm, which is suitable for scenarios where multiple operations are performed sequentially. However, the existing agricultural machinery scheduling and operating models have not fully considered the timeliness cost derived from the time requirements of field operation on agricultural machines, while the performance of the solving algorithms of the current model needs to be improved.

Based on the existing studies, we analysed the costs and benefits of mechanized harvesting scheduling to address various aspects of cereal crop harvesting using an order-oriented multi-machine collaborative operation as the subject, established a harvester operation scheduling model using the maximum operation income as the optimization goal, and proposed a simulated annealing genetic algorithm-based harvester operation scheduling algorithm to generate a reasonable agricultural machinery scheduling plan, improve the benefits and efficiency of agricultural machinery use, and provide a rational decision-making basis for agricultural machinery management.

MATERIALS AND METHODS

ANALYSIS AND ESTABLISHMENT OF THE HARVESTER OPERATION SCHEDULING MODEL

Analysis of the mode of harvester operation scheduling

In view of the characteristics and trends of agricultural machinery operation scheduling, this paper took the regional order-oriented multi-agricultural machinery cooperative scheduling model as the research object, and took the grain harvester as an example. The process of harvester operation scheduling under this model can be described as follows:

There is an agricultural machinery scheduling centre in a certain area, which has the functions of gathering statistics for agricultural machinery operation orders and coordinating the allocation of agricultural machinery resources within the region. During the harvest season, the centre collects agricultural machinery operation orders from farmers, including the type of operation, location coordinates of the operation, operation area, the earliest harvest time, and the latest harvest time, generates a harvester operation schedule for the region, and matches an appropriate harvester to each farm field according to the distance between each harvester and the field, the productivity and operation status of the harvester, etc.

Due to the complexity of the agricultural production environment, the research in this paper was based on the following assumptions:

(1) Information on farm operation orders and information on the location, operation capacity and status of harvester are clear, and the harvesters are not faulty during operation;

(2) Because the area of farmland is small and the distribution of farmland is scattered, the position information of farmland orders is represented by the latitude and longitude coordinates of the position where the harvester enters and exits the farmland;

(3) Single farm operation orders can be operated by one or more harvesters. When multiple harvesters work together, the agricultural machinery may come from different cooperatives. The harvesting time window required for the farmland operation order is the best harvest period of the grain;

(4) The harvester can reach the farmland operation point in advance, and the time for completing all the work in the farmland can slightly exceed the latest completion time specified in the order; However, it is necessary to calculate the cost loss caused by not operating in the time window specified by the order;

(5)The start time of each harvester in the same farmland is not necessarily the same, but the end time should be the same, and each harvester returns to the original hangar after completing all the order tasks.

Establishment of the harvester operation scheduling model

- **Model variables and parameter settings**

To analyse the harvester operation scheduling problem, it is necessary to mathematically describe the main variables and parameters involved in the scheduling process.

We defined the set $Ord=\{ord_1,ord_2,...,ord_M\}$ to represent M farmland order operation information, and single order operation information can be expressed as $ord_j=\{\{longitude_j, latitude_j\}, A_j, T_{sj}, T_{ej}\}, j=1,2,...,M$. Among them, $\{longitude_j, latitude_j\}$ represents the latitude and longitude position information of the order; A_j is the area of the field (hm^2); The operation time window starts from T_{sj} to the end of T_{ej}.

We defined the set $M_a=\{m_1,m_2,...,m_N\}$ to represent N harvesters, and each harvester can be expressed as $m_i=\{\{longitude_i, latitude_i\}, w, v\}$, $i=1, 2,...,N$. $\{longitude_i, latitude_i\}$ refers to the current location information of i harvester, including the parking locations in cooperative and operation point in farmland; w is the productivity of the harvester (hm²/h); v is the transfer speed (km/h).

We defined the set $P_r=\{V_s, G, D_{(g,h)}\}$ to represent the actual traffic road network information in reality. Among them, the set $V_s=\{V_{mo},V_f\}$ represents all the path nodes in the traffic road network, $V_{mo}=\{V_{m1},V_{m2},\ldots,V_{mK}\}$ represents the set of K cooperative location nodes, $K\leq N$; $V_f=\{V_{f1}, V_{f2},...,V_{fM}\}$ is the set of M farmland location nodes; the set $G=\{(g,h)/g, h\in V_s, g\neq h\}$ represents the linking arcs of all path nodes. The set $D_{(g,h)}=\{dist.(g,h)/g, h\in V_s\}$ represents the actual distance of the linking arc (g,h), calculated by the geographic coordinates of g and h.

The scheduling plan given by the scheduling centre includes the number of harvesters ordered by Field j (M_j), the ID number of each harvester, the time taken by Harvester i to reach Field j through Node g ($t_{i(g,j)}$), where $g, j\in V_s$, the actual starting time of Harvester i in Field j (t^i_{sj}), and the actual ending time of Harvester i in Field j (t_{ej}).

In addition, the following variables and parameters are included: F is the total income of the scheduling scheme (yuan); c_h is the revenue of the harvesting operations per unit area (yuan); c_{wj} is the cost of the harvester operations per unit area of Field j (yuan/hm²); c_d is the waiting time cost of the harvester per unit time (yuan/h); c_y is the harvester transfer cost per unit distance (yuan/km); c_s is the timeliness loss per unit area (yuan/hm²/h); x_{ij} is the flag of the harvester operation (when Harvester i operates in Field j, $x_{ij}=1$, otherwise, $x_{ij}=0$); $p_{i(g,h)}$ is the flag of harvester transfer (when Harvester i is transferred to Field h from Field g, $p_{i(g,h)}=1$, otherwise, $p_{i(g,h)}=0$).

- **Scheduling goals and constraints**

Through analysis of order-oriented multi-machine coordination scheduling, we constructed a harvester operation scheduling model with the operation income as the optimization goal, as follows:

$$\max F=(c_h-c_{wj})\sum_{j=1}^{M}A_j-c_y\sum_{i=1}^{N}\sum_{g\in Vs}\sum_{h\in Vs}p_{i(g,h)}D_{(g,h)}-c_d\sum_{i=1}^{N}\sum_{j=1}^{M}x_{ij}\max\left\{t_{i(g,j)}-T_{sj},0\right\}$$
$$-c_s w\sum_{i=1}^{N}\sum_{j=1}^{M}x_{ij}\max\left\{t_{ej}-T_{ej},0\right\} \tag{1}$$

Equation (1) is the objective function of the model, which calculates the income of the machine-harvesting operation in the area by subtracting the total cost from the total revenue of the machine-harvesting service. The total cost includes the operating cost, the transfer cost, the waiting time cost and the operation delay cost of the harvester.

By combining the production reality and relevant assumptions about the scheduling process, we placed the following constraints:

$$M_j=\left\lfloor\frac{A_j}{w[T_{ej}-T_{sj}]}\right\rfloor+1 \tag{2}$$

$$\sum_{i=1}^{N}\sum_{j=1}^{M}x_{ij}w(t_{ej}-t^i_{sj})=A_j \tag{3}$$

$$t_{i(g,h)}=t_{eg}+\frac{D_{(g,h)}}{v}<t_{eh} \tag{4}$$

$$\sum_{k\in V_{mo}}\sum_{g\in V_s}p_{i(k,g)}-\sum_{k\in V_{mo}}\sum_{g\in V_s}p_{i(g,k)}=0 \tag{5}$$

Equations (2)-(5) are the constraints of the model, of which equation (2) indicates the minimum number of harvesters required to complete the operation load of harvesting Field j; Equation (3) indicates the constraint that the operation load of harvesting Field j must be completed, in which t^i_{sj} is the time when Harvester i starts to operate in Field j; Equation (4) indicates that the time when Harvester i arrives at Field h is the sum of the time taken to complete operation in Field g and that taken for transfer from Field g to Field h and that this time should be earlier than the latest time that Field h needs to be harvested; Equation (5) indicates the constraint that Harvester i must return to its original garage.

SIMULATED ANNEALING GENETIC ALGORITHM-BASED HARVESTER SCHEDULING ALGORITHM

Selection of the harvester operation scheduling algorithm

The harvester operation scheduling problem can be regarded as a special case of a multi-parking lot vehicle scheduling problem with a time window, which is a rather complicated combinatorial optimization problem *(Santoro et al., 2017)*. Intelligent heuristic algorithms such as Genetic algorithm (GA) *(Gholami et al., 2018)*, Simulated Annealing algorithm (SA) *(Cruz-Chávez et al., 2017)*, Ant Colony Optimization *(Engin and Güçlü, 2018)* and Tabu Search algorithms *(Dabah et al., 2019; Qiu et al., 2018)* have been widely used to solve similar large-scale scheduling problems. Among them, simulated annealing genetic algorithm is a hybrid optimization algorithm that combines genetic algorithm and simulated annealing algorithm. It adopted the original genetic algorithm coding method, which can keep the original global parallel search ability of genetic algorithm *(Liu et al., 2014; Song et al., 2020)*. The simulated annealing operation in the algorithm can give full play to the excellent local search ability of simulated annealing algorithm, overcome the disadvantage of poor local search ability of genetic algorithm, make the algorithm jump out of the local optimal solution region and search for the global optimal solution *(Zheng et al., 2020)*; Therefore, we designed a harvester operation scheduling algorithm based on simulated annealing genetic algorithm, in order to improve the responsiveness of the harvester scheduling system while increasing income of the machine-harvesting operation.

Coding for the solution

By combining the characteristics of the harvester operation scheduling problem and the results of related studies, we used a two-layer coding method for the solution, as shown in Fig.1.

F_1		F_2			F_3			F_4		F_5	
m_1	m_2	m_3	m_4	m_5	…	…	…	…	…	m_{k-1}	m_k

Fig. 1 - Coding structure

The first layer of the coding is to sort the fields, in which the order of the fields is the service order of the field operation orders; in Fig. 1, F_1 - F_5 are field operation orders. The second layer of the coding sorts the harvesters in the fields, e.g., in Fig. 1, harvesters m_1 and m_2 are operating in Field F_1.

Generation of the initial solution based on scheduling rules

In traditional genetic algorithm, the initial population is mostly constructed by random generation, which may produce a large number of poor-quality solutions or illegal solutions for scheduling problems with time windows. In order to avoid the generation of invalid solutions and improve the efficiency of the algorithm, the initial solution is generated based on scheduling strategy.

- **scheduling strategy**

According to production experience, prioritizing the service to fields that have an approaching harvesting time window and a large area can lower the loss caused by harvesting delay, and reasonably allocating harvesters for different fields can reduce production cost. Therefore, we used the following strategies when coding:

Strategy 1: The priority function was designed with the weighting method using the field time window and field area as variables, and the field operation order was decided based on the priority.

Assuming that the weight of the time window factor is w_1, that of the field area is w_2, and t and a are the normalized data of the field time window and field area, respectively, we obtained the priority function as shown in Equation (6).

$$f = w_1 t + w_2 a \tag{6}$$

Strategy 2: The field is matched with the minimum amount of agricultural machinery resources that can meet the production needs. The number of harvesters assigned to a field is determined by the area of the field and the harvesting time window, using Equation (2).

Strategy 3: When matching the field operation order with harvesters, the harvester with the lower absolute difference between the arrival time and the earliest harvesting time of the field is preferentially scheduled.

- **Initial population generation algorithm**

Based on the above coding strategies, the initial solution of the simulated annealing genetic algorithm was generated, with the following steps:

Step 1: Establish a field operation set and rank the operation order according to Strategy 1; establish the operating harvester set;

Step 2: Determine whether the field operation set is empty. If the set is empty, go to Step 4, otherwise, go to Step 3;

Step 3: Assign harvesters to field operation orders according to Strategies 2 and 3; go to Step 2;

Step 4: The matching for the initial scheduling scheme is completed. The initial population with a certain number of chromosomes is generated by random variation of genes in the initial scheme.

Fitness function

Since the optimization goal of the harvester scheduling model is to maximize the operation income of harvesters, the Equation (1) can be directly used to calculate the fitness of each chromosome.

Genetic manipulation

- **Selection operator**

The selection operation in the algorithm adopted the roulette method. The greater the fitness of the individual is, the greater the probability of each chromosome being selected, which ensures that good individuals have a greater chance of being retained and participating in evolution.

- **Crossover operator**

We used the mutated partially mapped crossover to cross the selected parent individuals to increase the proportion of feasible solutions. The basic operation is as follows: two crossover points are randomly generated in the upper farmland code, and then the agricultural machinery codes of the lower layer corresponding to the two crossing points in the parent individuals A1and A2 are exchanged to generate new individuals B1 and B2. The specific cross processing is shown in Fig.2:

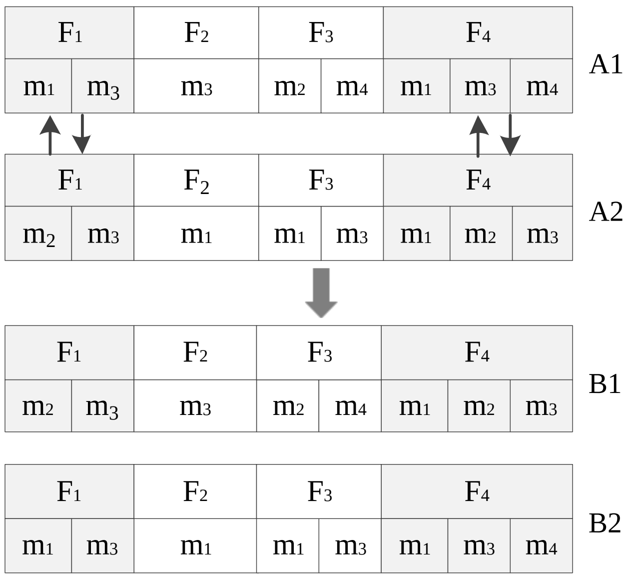


Fig. 2 - Chromosome crossover

- **Mutation operator**

Mutation operation is an important means to ensure the diversity of population. The basic operation of mutation operator in this paper was as follows: randomly generated a mutation point in the selected individual farmland code, and randomly mutated an agricultural machinery code in the lower layer of the selected farmland code to generate a new individual.

Simulated annealing operation

- **Cooling function**

Simulated annealing operation is the simulation of thermodynamic annealing process. In the simulated annealing process, every time the temperature is lowered, the algorithm completes an optimization, and the number of iterations is equal to the number of temperature drops. The simulated annealing cooling formula is:

$$T_k = r^k \cdot T_0 \tag{7}$$

In Equation (7), T_k is the current temperature; r is the cooling coefficient, $0 < r < 1$; k is the number of cooling; T_0 is the initial temperature; all variables in this equation are dimensionless. The number of cooling times k is the current iteration number of the algorithm.

- **New solution acceptance criteria**

In the iterative process of the algorithm, new solutions are generated through the crossover and mutation operations mentioned above. The objective function values of the new solution X_2 and the old solution X_1 are $F(X_2)$ and $F(X_1)$ respectively, and the difference between $F(X_2)$ and $F(X_1)$ is defined as $\Delta E= F(X_1)- F(X_2)$. The probability of accepting the new solution is calculated using Metropolis criterion:

$$P_{T_k} = \min\{1, e^{-\frac{\Delta E}{T_k}}\} \tag{8}$$

In Equation (8), P_{T_k} is the probability of accepting the new solution; T_k is the current temperature, and all variables are dimensionless.

Overall algorithm steps

The overall process of the simulated annealing genetic algorithm-based harvester operation scheduling algorithm is as follows:

Step1: Read the order information of the farmers and the position coordinate information of the harvesters; initialize the distance matrix; establish the field operation task set and prioritize the tasks; establish the harvester set.

Step2: Initialize the parameters. Parameters include annealing initial temperature T_0, termination temperature T_{min}, cooling rate r, population size S_{pop}, evolution termination algebra M_{gen}, crossover probability P_c, mutation probability P_m, etc.

Step3: According to the various parameters in the scheduling model: order information of farmland, initial state information of each harvester, distance matrix of each coordinate point and other information, use priority rules to generate the initial population, and calculate the fitness value of each individual X_i, i= 1, 2, ... , S_{pop}. Record the global optimal solution as X_{best}=maxX_i; set the current temperature $T=T_0$;

Step4: Set the genetic loop count variable gen=0.

Step5: Perform selection, crossover, and mutation operations on the population to form a new population individual and calculate the fitness value X_i, i=1,2,..., S_{pop}, and record the current optimal solution X_{new}=maxX_i.

Step 6: calculate$\Delta E=X_{best} - X_{new}$, if $\Delta E<0$, $X_{best}=X_{new}$; otherwise, calculate the acceptance probability P_{tk} of new solution X_{new} according to the new solution acceptance criteria in 2.6 and judge whether to make $X_{best} = X_{new}$.

Step 7: judge whether $gen< M_{gen}$ is true, if yes, then gen = gen + 1 and go to step 5; otherwise, go to step 8.

Step 8: judge whether $T < T_{min}$ is true, if so, the algorithm will terminate and get the global optimal solution X_{best}; otherwise, execute the cooling operation$T_{k+1}=T_k r$, and turn to step 4 until $T<T_{min}$ holds.

RESULTS

Case information

In this paper, four agricultural machinery cooperatives in Wuchang City, Heilongjiang Province, China were selected as the analysis objects, numbered O1-O4. The cooperatives had 10 harvesters. The Agricultural Machinery Operation Scheduling Centre received a total of 20 farmland rice harvesting orders during the harvest season, and all orders were completed by four cooperatives. The specific information of farmland orders and harvesters are shown in Tables 1 and 2.

Table 1

Farmland job order information

Farmland number	East longitude [°]	North latitude [°]	Area [hm^2]	Time window
1	127.1594	45.1222	34.20	10.1-10. 4
2	127.1750	44.5621	16.40	10.1-10. 3
3	126.8755	44.4111	27.87	10.2-10.5
4	127.7832	45.2904	23.60	10.2-10. 5
5	126.7959	44.9090	30.67	10.2-10. 6
6	127.1191	44.5549	22.80	10.3-10.6
7	126.7471	45.1648	31.07	10.3-10.7
8	126.9162	44.3555	36.13	10.3-10.7
9	127.5360	44.9858	24.20	10.4-10.7
10	127.2267	44.9844	25.40	10.5-10.8
11	127.0565	44.8796	39.67	10.5-10.9
12	126.9382	45.0852	25.47	10.5-10.9
13	126.9322	45.0250	19.80	10.6-10.10
14	127.4192	44.6940	37.80	10.6-10.10
15	126.8195	45.1222	33.53	10.7-10.11
16	127.5845	45.2773	14.73	10.7-10. 10
17	127.2102	44.8170	32.40	10.8-10. 12
18	127.0675	44.7754	30.40	10.8-10. 12
19	127.2927	44.8396	21.07	10.9-10. 14
20	127.6055	45.1611	35.73	10.9-10. 14

Table 2

Agricultural machine descriptions

Harvester number	East longitude [°]	North latitude [°]	Transfer speed [km/h]	Productivity [hm^2/h]
M1	127.0841	45.0843	35	0.45
M2	127.0841	45.0843	35	0.45
M3	127.1765	44.8246	35	0.45
M4	127.1765	44.8246	35	0.45
M5	127.1765	44.8246	35	0.45
M6	127.4425	45.0242	35	0.45
M7	127.4425	45.0242	35	0.45
M8	127.4425	45.0242	35	0.45
M9	127.5586	44.9168	35	0.45
M10	127.5586	44.9168	35	0.45

Through relevant research and data review, the service price of Wuchang City is 900 yuan/hm^2, and the Kubota 4LBZ-172B semi-feeding harvester was used for operation. The operating cost of the harvester was 720 yuan/hm^2 (excluding fuel cost), the harvester can work for 12 hours a day, the transfer speed was 35 km / h, the transfer cost was 4 yuan/km, the waiting cost was 42 yuan/h, harvester hourly productivity was 0.45 hm^2/h, the operation delay cost of the harvester was 10.8 yuan/hm^2/h, and the actual transfer distance between each coordinate point was obtained through the Baidu map API interface.

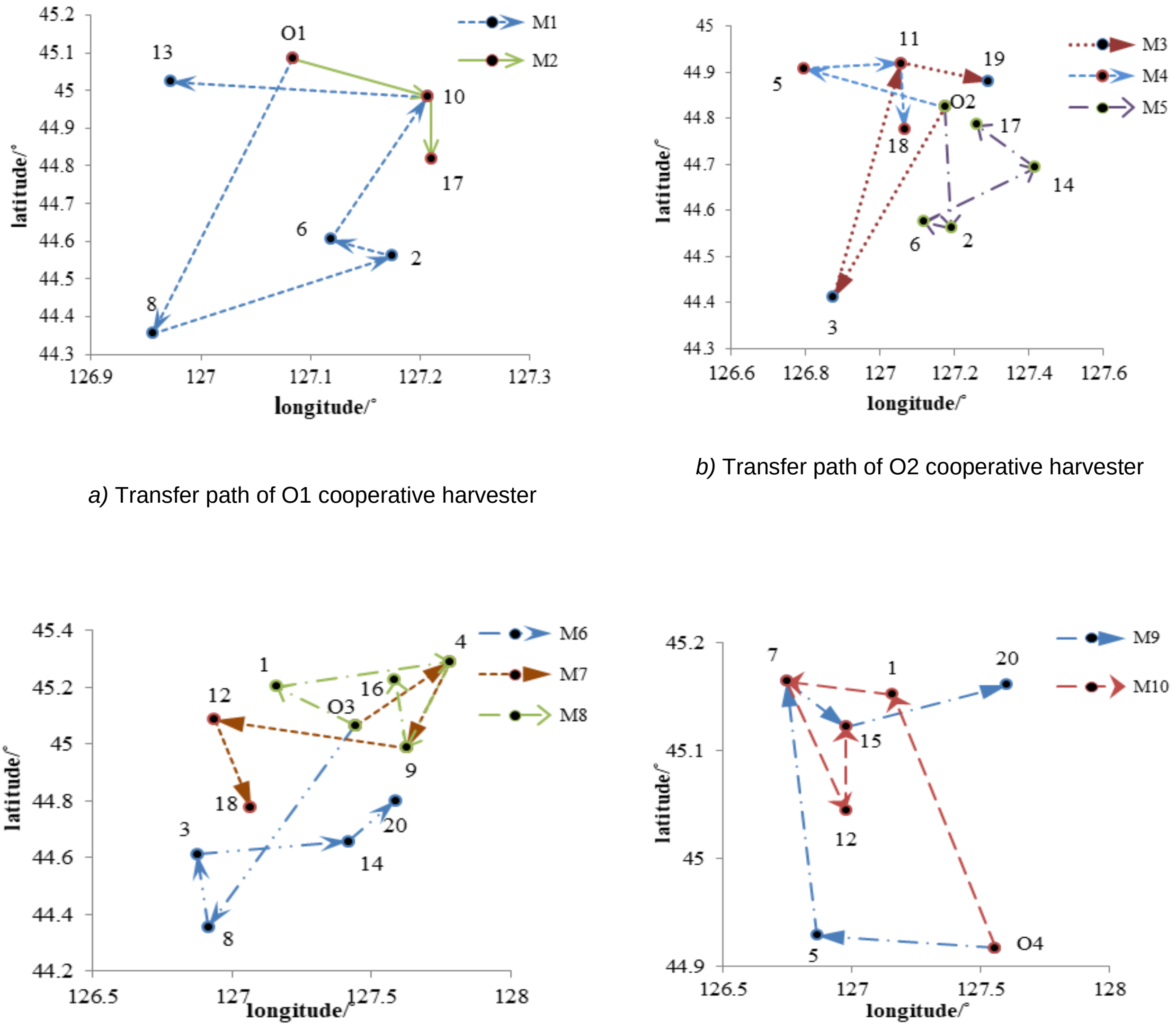
RESULTS AND DISCUSSION

The proposed simulated annealing genetic algorithm-based harvester operation scheduling algorithm was implemented using MATLAB R2019a software on a PC with Windows10. In the experiment, the parameters of the simulated annealing genetic algorithm were as follows: initial temperature T_0 = 100, termination temperature T_{min} =10^{-20}, cooling rate r = 0.85, population size S_{pop}=30, evolution termination algebra M_{gen}=20, crossover probability P_c=0.8, mutation probability P_m=0.2.

This example was solved using the proposed simulation annealing genetic algorithm with MATLAB software to obtain the scheduling scheme, as shown in Figs. 3 and 4.

Fig. 3 shows the transfer paths of harvester operation, the locations of the agricultural machinery centres and fields were described through coordinates, in which the abscissa is the longitude, and the ordinate is the latitude. The harvester transfer path of each harvester of each centre can be obtained using the proposed algorithm.

For example, Fig. 3a shows that the harvester transfer path of Harvester M1 from Centre O1 was 8-2-6-10-13. It can be seen from the Fig. 3 that all the orders were serviced and there was spatial proximity between the order tasks assigned to each harvester, which indicated the rationality of the experimental results.



a) Transfer path of O1 cooperative harvester

b) Transfer path of O2 cooperative harvester

c) Transfer path of O3 cooperative harvester

d) Transfer path of O4 cooperative harvester

Fig. 3 - Diagram of each harvester's job transfer path

Figure 4 shows the harvester operation scheduling Gantt chart, in which:

- the abscissa is time;
- the ordinate is the harvester ID number;
- the bar represents the operation plan of each harvester in the field, including the order number, the operation start time, and the operation end time.

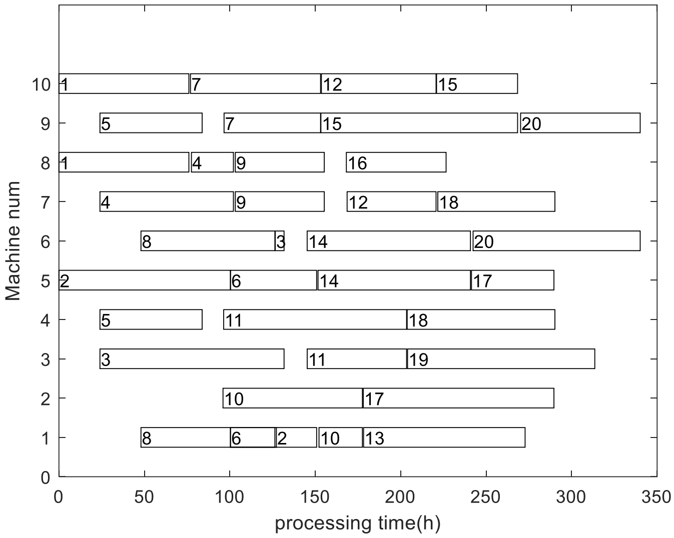


Fig. 4 - Deployment of Gantt chart

To further illustrate the validity of the algorithm, we ran 20 iterations using SA, GA and SAGA respectively, and compared each of the variable cost indicators of the scheduling schemes obtained. The results are shown in Table 3.

Table 3

The comparison of 3 algorithms scheduling results

Income and cost indicator	SA	GA	SAGA
The operation income (yuan)	94027.40	92816.07	94414.73
The transfer distance (km)	1669.81	1728.13	1602.92
The waiting time cost (yuan)	0	456.12	0
The operation delay cost (yuan)	671.07	1234.73	541.70

Table 3 shows that the operation income of the scheduling scheme generated using the proposed algorithm increases by 387.33 yuan and 1598.66 yuan on average compared with SA and GA alone, indicating that the SAGA was superior in improving the income from the harvesting operation. Compared with those of the scheme obtained through the SA and GA, the transfer distance of the scheme obtained through the SAGA decreased by 4.0% and 7.25% on average. SA and GA can obtain the scheduling scheme with a waiting time of 0 hours. In addition, the scheduling scheme calculated by SAGA also had the minimum average operation delay cost, which were 19.28% and 56.1% lower than those of SA and GA respectively. The experimental results showed that the harvester scheduling algorithm based on SAGA can better meet the constraints of time window, and reduce the costs related to scheduling, so as to obtain the highest operation income.

Algorithm performance analysis

To further evaluate the stability, search performance and running efficiency of the harvester operation scheduling algorithm designed in this paper, based on the cases obtained from the investigation, five calculation examples with different numbers of farmland were constructed. We used simulated annealing algorithm, genetic algorithm and simulated annealing genetic algorithm to conduct 20 simulation tests for 5 cases respectively. The experimental results are shown in Fig. 5 and Fig. 6.

Fig. 5 shows the average operation income and standard deviation of the scheduling scheme obtained by three algorithms for five different calculation examples. The SAGA can obtain the maximum average operation income in all the calculation examples, and in the first four examples, SA obtained better average operation income than genetic algorithm. Among the three algorithms, the standard deviation of the operation income calculated by genetic algorithm was the largest in all calculation examples, which proved that the solution of genetic algorithm had greater fluctuation. When SAGA was used to solve the calculation examples of 20, 60, 100 farmland, the standard deviation of the operation income was the smallest.

The experiment confirmed that the proposed algorithm had good stability and can obtain high-quality solutions for various examples, with only small fluctuations.

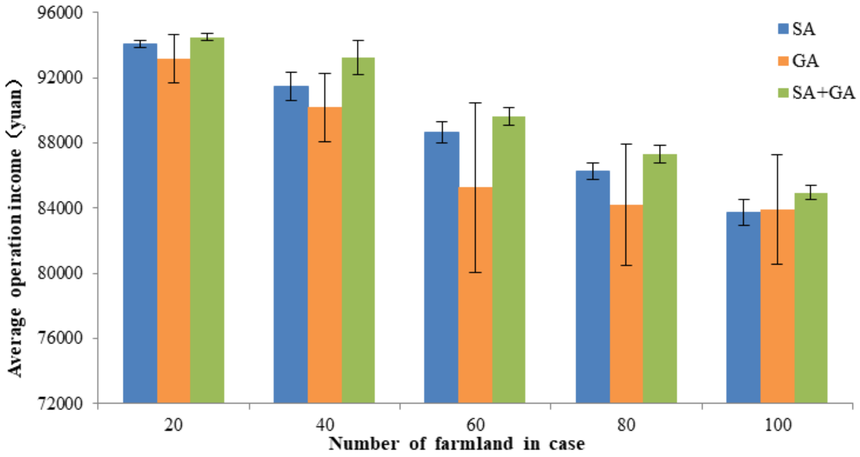


Fig. 5 - The average and variance of operation income

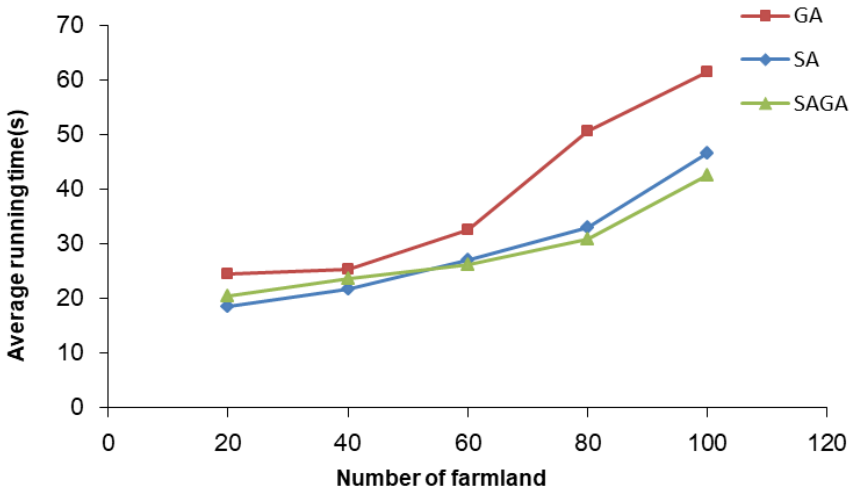


Fig. 6 - The average running time of three algorithms

Fig. 6 shows the average running time of the scheduling scheme obtained by three algorithms for five different calculation examples. With the increase of the number of farmlands in the calculation examples, the average running time of the three algorithms increased, which was caused by the increase of the complexity of the problem. GA had the longest running time, which may be related to its use of randomly generated initial population as the starting point of evolution. The SA and SAGA use the rule-based initial solution algorithm to obtain the initial solution which is a better beginning of optimization and greatly shorten the running time of the algorithm. In the last three calculation examples, the average running time of SAGA is less than that of using SA only, and the time saved was increasing, which showed that the genetic operation introduced in SAGA can improve the search efficiency of the algorithm in large-scale cases. At the same time, when the number of farmlands in the case was 100, the running time of the SAGA was only 42.55 s, which can meet the demand of large-scale farmland case scheduling in reality.

CONCLUSIONS

(1) In this study, we analysed each cost item generated in harvester operation scheduling using order-oriented multi-machine collaborative operation scheduling as the subject and constructed a harvester operation scheduling model using the total income of the harvesting service as the optimization goal. This model effectively integrated the information about the operating cost, transfer cost, waiting time cost, and the operation delay cost of the harvesters and improved the accuracy of the harvester operation scheduling model.

(2) By analysing and comparing the advantages and disadvantages of existing vehicle scheduling algorithms, combining with the characteristics of harvester scheduling, we combined genetic algorithm with simulated annealing algorithm and proposed a simulated annealing genetic algorithm-based heuristic harvester operation scheduling algorithm.

(3) We performed example simulations and related experimental analyses using MATLAB software to analyse the effectiveness, stability, search performance and running efficiency of the proposed harvester operation scheduling algorithm. The experimental results showed that the proposed harvester operation scheduling algorithm effectively combined the good global search performance of the GA and the strong local search capability of SA, and can be superior to the existing algorithm in meeting the demand of farmland time window and increasing operation income. Moreover, the proposed algorithm had higher stability, less fluctuation of solution quality and faster running efficiency, which made it possible to solve large-scale farmland scheduling problems.

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