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Agricultural Machinery Inter-regional Cooperative Job Scheduling Method based on An Improved SPBO Algorithm

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Abstract

Given the lack of scientific and reasonable optimization scheduling strategies, multimachine cross-regional operations often encounter high operation costs, low operation efficiency, and the inability to complete farmland tasks within the suitable operation time during the harvest season. To address this issue, the authors of this study constructed a multimachine cross-regional collaborative operation scheduling model under the constraint of operation time windows to minimize the transfer distance cost of agricultural machinery operations and the total scheduling cost. An improved standard particle swarm optimization (SPBO) algorithm was designed, a double-layer coding method was adopted to encode genes, and an individual repair strategy was designed during decoding to reduce the number of iterations. Three evolutionary operators, namely, strong disturbance, weak disturbance, and learning strategies, were introduced to enhance the algorithm's local and global search capabilities. According to the priority rule of time windows, combine harvesters were allocated for operations in sequence, and a reoptimization strategy was adopted. An improved SPBO algorithm with the addition of worst removal and greedy insertion operations for orders was proposed as the scheduling optimization algorithm. Simulation experiments and comparative analysis verify that, the improved SPBO algorithm proposed in this study can effectively avoid local optimal problems, accelerate the global convergence speed, and avoid the waste or redundant use of resources, thereby reducing costs. The conclusion provides a new solution for the path planning problem of cross-regional collaborative operations of agricultural machinery.

Keywords: Agricultural machinery, Collaborative operation, Time window, Improved SPBO algorithm

1. Introduction

With the continuous emergence of new types of production and operation entities in China, modern agricultural production models such as large-scale operations have begun to rise, thereby driving an increase in the demand for agricultural machinery socialized services [1]. In China, the cultivated land in most regions is geographically fragmented, and scattered farmers remain the main body of agricultural production. Farmers' income largely depends on the yield and market price of agricultural products. The on-demand use of agricultural machinery can help farmers increase crop yields and income [2]. However, agricultural machinery is expensive, and small farmers can hardly afford it. Usually, only farmers with more land purchase agricultural machinery to meet the needs of crop harvesting [3]. During the busy farming season, the "shared agricultural machinery" model of cross-regional operation with harvesters is the most effective way to provide on-demand and low-cost services for scattered farmers [4]. Wheat is the main food source for nearly half of the residents in Asia. In China, wheat production accounts for more than one-fifth of the country's total grain production. The maturity period of wheat varies due to geographical location, resulting in the cross-regional migration of wheat harvesters from south to north as the crops mature. Therefore, the cross-regional dispatch of agricultural machinery has strong spatiotemporal evolution characteristics and resource constraints [5]. Currently, the cross-regional dispatch of agricultural machinery mainly relies on human experience, and the dispatch plans lack reasonable planning based on the maturity period of crops. Problems such as disorderly operation area sequences and unreasonable allocation of agricultural machinery resources lead to low operation efficiency, delay of farming time, and reduction of crop harvest yield and quality. Therefore, based on the demand for cross-regional operation of agricultural machinery during the "Three Summers" (summer harvest, summer sowing, and summer management) period, studying the allocation of agricultural machinery resources under multiple constraints is crucial to improving the efficiency of cross-regional operation of harvesters and ensuring operation quality.

2. State of the art

In recent years, scholars have conducted extensive research on agricultural machinery scheduling problems from various perspectives, mainly focusing on transforming the problem into a VRP problem with time windows or a transportation problem in operations research. Sugianto et al. [6] comprehensively considered multiple optimization objectives, such as the operation duration, operation cost, and operation quality of agricultural machinery, and designed a multiobjective particle swarm optimization algorithm based on time windows. They adopted an adaptive grid method and roulette wheel selection method to select particles, thereby enhancing the efficiency of agricultural machinery operation scheduling. Zakir et al. [7] addressed

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the issues of easy convergence to local optimal solutions and low operational efficiency when using the NSGA-II algorithm to solve the multi-UAV cooperative detection task and established a multiobjective optimization function aiming for maximum detection profit and minimum energy consumption and flight distance. They proposed the TS-NSGA-II algorithm. Shang et al. [8], combined the tabu search algorithm to add the new population obtained to the elite retention strategy of the NSGA-II algorithm. Compared with the NSGA-II algorithm, the TS-NSGA-II algorithm can obtain better Pareto solutions and has remarkable advantages in convergence Liu et al. [9] adopted the NSGA-III algorithm to solve the multiobjective path planning problem of pesticide spraying in greenhouses, optimizing the robot's travel distance and travel path angle, effectively reducing the cost of the robot's operation path. Giesen et al. [10] aimed at the problem of poor local search ability and premature convergence of traditional genetic algorithms in UAV path planning with obstacles. On the basis of the NSGA-II algorithm, they adopted an adaptive adjustment of crossover and mutation probabilities and designed a directional convex mutation strategy to replace the random mutation mechanism, effectively reducing the risk of falling into local optima and improving the convergence speed of the algorithm.

At present, research hotspots are mostly focused on single-task or small-area scheduling, usually considering only one agricultural machinery supply point or the same type of agricultural machinery. Commonly used scheduling optimization objectives in agricultural machinery scheduling research include maximum operation income [11], minimum total scheduling cost [12], and minimum scheduling distance [13]. The agricultural machinery scheduling problem belongs to NP-hard problems. When encountering large-scale computing instances, NP-hard problems cannot be solved within an effective time, and heuristic algorithms are often used for solutions [14]. For instance, Tang et al. [15] combined the simulated annealing algorithm, genetic algorithm, and hybrid Petri net model and proposed a two-stage metaheuristic algorithm to solve the resource allocation and scheduling model for sugarcane production and harvesting, achieving a high resource utilization rate. Ibarra-Rojas et al. [16] aimed to minimize the working time of agricultural machinery and proposed a planning method to determine the sequence of biomass harvesting and processing operations, solving the scheduling problem of sequential processing of biomass in multiple fields. Schobel [17] aimed to maximize the total service area of harvesters and proposed an ALNS metaheuristic algorithm to solve the scheduling problem of sugarcane harvesters with time windows. Deveci et al. [18] analyzed various costs of agricultural machinery scheduling and established an agricultural machinery scheduling model under major epidemic situations with the objective of minimizing the total scheduling cost; moreover, they improved the simulated annealing algorithm to solve the model. The above studies all focused on the optimization of field paths within a region. During the busy farming season, farmers' operation demands often come from different provinces, cities, and counties, with spatial spans ranging from tens to hundreds of kilometers. Large-scale cross-regional scheduling of various types of agricultural machinery over a large spatial scale can better meet the needs of agricultural production. Some studies on cross-regional agricultural machinery scheduling have been conducted. For example, Dominguez-Martin et al. [19] established an emergency cross-regional operation scheduling model for agricultural machinery with the objective of minimizing the allocation cost and loss and proposed two algorithms for solution. Drexl et al. [20] solved the static partitioning and dynamic cross-regional collaborative scheduling problem of agricultural machinery through an improved nondominated neighborhood search algorithm and tabu search algorithm. Goel et al. [21] studied the cross-regional operation of agricultural machinery considering multiple depots, multiple machine types, and operation time windows, improving the punctuality rate of services and the utilization rate of agricultural machinery. Heil et al. [22] considered the infection status of pests and diseases in the fields, sorted orders and conducted scheduling operations, and used the nondominated sorting genetic algorithm to plan the multiobjective operation paths of agricultural drones. To break through the limitations of multiobjective optimization problems when the same type of drones is operating, Koc et al. [23] comprehensively considered the convergence and particle distribution issues of the traditional particle swarm algorithm, designed a multilayer coding strategy and constraint scheduling method, and improved the evaluation method of solutions, reasonably retaining some special boundary solutions. Compared with traditional algorithms, this method can better handle constraints and improve the quality of solutions. Pessoa et al. [24] introduced the adaptive acceptance criterion in the simulated annealing algorithm into the genetic algorithm to obtain multiobjective optimized vegetable delivery paths. The above collaborative operation scheduling studies are mostly concentrated in the fields of emergency material allocation, logistics distribution, and drone operation scheduling, with relatively few studies on the scheduling problem based on the collaborative operation of agricultural machinery in the fields.

In summary, this study comprehensively considers the factors of farmland operation time window, plot location, and transfer cost and studies the optimization scheduling problem of multimachine inter-regional cooperative operation with the goal of minimizing the transfer distance cost and total dispatch cost of agricultural machinery. By constructing the optimal model of cross-regional scheduling and designing the optimal scheduling algorithm, a scientific and feasible scheduling scheme is provided for the multimachine cooperative operation of agricultural machinery cooperatives.

The rest of this study is organized as follows. The section 3 provides 3. Methodology, including problem description and model construction. Section 4 describes the result analysis and discussion. Section 5 summarizes the conclusions.

3. Methodology

This study constructs a multi machine cross regional collaborative job scheduling model. In order to solve the model, three evolutionary operators, strong perturbation, weak perturbation, and learning strategy, are introduced to improve the algorithm's local and global search capabilities. A design is proposed to improve the standard student psychological optimization algorithm (SPBO). This section will provide a detailed introduction to the model constructed and the algorithm designed.

3.1 Model building

3.1.1 Problem description

China has a vast territory, and wheat crops mature from south to north in sequence. This pattern provides a continuous working window for agricultural machinery. However, the distribution of agricultural machinery resources in China is uneven in geographical space. During the busy farming season, farmers often lease harvesters from other regions to complete the harvesting tasks. Usually, a few farmers rely on social trust and relationship networks, often based on empirical data, to convey demand information orally or by phone to the agricultural machinery drivers to complete the cross-regional mechanical harvesting of wheat. However, this model overly depends on personal relationships and has low dispatching efficiency, easily causing a mismatch of resources and information. In large-scale agricultural machinery dispatching, the dispatching model involving agricultural machinery cooperatives is the main way to complete the cross-regional mechanical harvesting of wheat during the “Three Summers” period. During the cross-regional operation of harvesters, farmers’ operation demands often come from different provinces, cities, and counties. After receiving operation orders containing information such as the type, area, and location of the farmland, the cooperatives dispatch the harvesters. The harvesters are transported in a convoy by trucks from the cooperatives to the areas to be harvested. Then, they complete the harvesting tasks.

This problem considers a cooperative providing cross-regional operation service of harvesters for multiple wheat harvest areas, and each cooperative has multiple, same-model combine harvesters. The real environment and influencing factors of agricultural machinery field operations are complex and changeable. The following assumptions are made to facilitate research:

(1) The types and operation capabilities of agricultural machinery in the cooperatives are the same, and the speed of agricultural machinery during transfer is constant.

(2) In this study, the situation of agricultural machinery failure is not considered, and only one piece of agricultural machinery is allowed to provide operation services at one farmland operation point.

(3) After completing all the operation tasks on the current path, the agricultural machinery returns to the agricultural machinery cooperative.

(4) The transportation rate and working efficiency of the same model of harvesters are the same. The transportation of harvesters from the cooperative to the harvest area is only by road, and weather conditions, road congestion, and road capacity restrictions are not considered.

(5) The locations of the agricultural machinery cooperatives, the harvest areas, and the areas to be harvested in the harvest areas are known. The time when the harvester group arrives at the harvest area is the start of the harvest time, and the quality and yield of wheat within the harvest time window are constant.

3.1.2 Model construction

In this study, the relevant variables are described as follows: farm operation point set $N=\{1,2,3,\cdots, i\}$, where i is any operation point. The farmland area of $S=\{S_1,S_2,S_3,\cdots,S_i\}$, S_i is the area of the i farmland operation point (km^2), $i \in [1,30]$. Agricultural machine set $M=\{1,2,3,\cdots, k\}$, where k is agricultural machine, whose performance parameter is expressed as $P=\{P_k, V_{kt}, V_{ko}, C_{kt}, C_{kw}, C_{ko}, W_i^k\}$, where P_k represents the working efficiency of agricultural machinery per unit time, km^2/h; V_{kt} indicates the operation transfer speed of agricultural machinery per unit time, km/h; V_{ko} represents the operating speed of agricultural machinery per unit time, km/h; C_{kt} represents the transfer cost of agricultural machinery k within a unit distance, yuan /km; C_{kw} indicates the penalty cost of waiting operation of agricultural machinery per unit time, yuan/h; C_{ko} represents the operation cost of agricultural machinery k per unit area, yuan/km^2; W_i^k represents the total waiting time of machine k in field i, $k \in [1,10]$. ρ_i^k represents the control variable; when the value of ρ_i^k is 1, it means that the agricultural machine k generates the waiting time t at the operation point i, and when the value of ρ_i^k is 0, the agricultural machine k does not generate the waiting time. D_{ij}^k represents the transfer distance between farmland and the transfer distance between agricultural machine k starting from farmland i to farmland j. TW_i represents the operating time window for field i. e_i indicates the earliest time field i allows farm machines to operate. e_i indicates the earliest time field i allows the farm machine to operate. l_i indicates the latest time when the farm machine completes the field i task. C refers to the commissioning cost of agricultural machinery. r_i indicates the actual start time of the harvest operation of the farm machine. The objective function is given, aiming at the situation of k agricultural machines performing job scheduling at i farmland operation points, as shown in Equation (1). Formula (1) is the lowest total cost of agricultural machinery scheduling as the optimization objective, in which the first item is the fixed cost of agricultural machinery, the second item is the operational cost of agricultural machinery, the third item is the route transfer cost of agricultural machinery, and the fourth item is the waiting operational cost of agricultural machinery.

$$minD = c\sum_{i,j\in I}\sum_{k=1}^{K} x_{ij}^k + \sum_{i=1}^{I}\sum_{k=1}^{K} C_{k0}S_i + \sum_{i=1}^{I}\sum_{k=1}^{K} C_{kt}D_{ij}^k + \sum_{i=1}^{I}\sum_{k=1}^{K} \rho_i^k C_{kw}W_i^k \tag{1}$$

S.T.

$$e_i \text{ Ñ } r_i \text{ Ñ } l_i, \forall i \in N \tag{2}$$

$$\sum_{i\in I}\sum_{k=1}^{K} x_i^k = 1 \tag{3}$$

$$\rho_i = \begin{cases} 1, yes \\ 0, no \end{cases} \tag{4}$$

$$x_{ij}^k = \begin{cases} 1, machine\ k\ passes\ i\ to\ j \\ 0, machine\ k\ does\ not\ pass\ i\ to\ j \end{cases} \tag{5}$$

The working environment of agricultural machinery is complex to facilitate the investigation of constraints in this study; thus, the following provisions are made. Formula (2) represents the appropriate working time window for field operation point i, including the earliest time suitable for starting work and the latest time suitable for completing work. The agricultural machinery should arrive at field operation point i within the task window e_i Ñ r_i Ñ l_i. Formula (3) indicates that each field operation point has only one agricultural machine. Formula (4) indicates that the waiting time will be generated when the agricultural machine k arrives at the working point i before the earliest start of the operation; otherwise, no waiting time will be generated. (5) is the decision variable.

3. 2 Algorithm design

3.2.1 Coding

This study selects the real number sequential coding method. N areas must be harvested, with odd points representing the nodes of agricultural machinery cooperatives and even points representing the nodes of areas to be harvested. There are M agricultural machinery cooperatives, and each supply point can dispatch up to K agricultural machinery wheat harvesters to provide wheat harvesting services. The N areas to be harvested are respectively marked as 1, 2, 3,..., N−1, N. For any supply point's K vehicles, they are marked with the same number. The vehicle numbers of the M agricultural machinery cooperatives are N+1, N+2, N+3,..., N+M. Thus, the length of an individual chromosome is L=N+M*K, where genes with numbers less than or equal to N represent areas to be harvested, and genes greater than N represent the agricultural machinery dispatched by different agricultural machinery cooperatives. Assuming N = 20, M = 1, and K = 1, then, L = 20 + 1*1 = 21.

This coding method mainly targets the agricultural machinery scheduling problem involving multiple areas to be harvested and agricultural machinery cooperatives and is particularly suitable for situations where multiple agricultural machinery or agricultural machinery cooperatives need to be scheduled. Its main feature is that each agricultural machinery has an independent service path (represented by genes), which is conducive to handling the scheduling problem of multiple agricultural machinery or agricultural machinery cooperatives simultaneously and can effectively deal with the situation where the number of agricultural machinery is limited; moreover, it is especially suitable for large-scale agricultural machinery scheduling tasks. In this coding method, the relationship between multiple areas to be harvested and agricultural machinery cooperatives is clear, and it is especially suitable for the scenario of concentrated wheat harvesting during the wheat harvest period. When the number of vehicles is small, this coding method can also clearly express the service path of each agricultural machinery. In addition, this coding method can adapt to different types of agricultural machinery harvesting needs (such as rice harvesting agricultural machinery scheduling, corn harvesting agricultural machinery scheduling, agricultural machinery plowing scheduling, etc.). By using the numbers in the genes to represent the service paths of agricultural machinery, the service sequence can be flexibly adjusted, and it can easily be embedded into optimization algorithms, further enhancing the applicability and flexibility of the model.

3.2.2 Population restoration strategy

In accordance with the above coding, the initial population is generated as n combinations of $\{1,2,...,n,\ n+1,\ldots,\ n+k\}$ arbitrary random sequences. Given that agricultural machinery scheduling requires route order restriction to be arranged in accordance with orders received by agricultural machinery cooperatives and individuals may be produced in random initial populations that do not meet the order restriction, the illegal coding must be repaired, and the individual repair strategy is as follows:

(1) All genes are uniformly distributed and randomly generate nonrepeating natural numbers within the $\{1,2,...,n,\ n+1,\ldots,\ n+k\}$ interval, in which the first gene location of an individual must be the "vehicle gene";thus, repair operations must be performed before the population individual decoding.

(2) The route length of each agricultural machine is determined, each waiting area must be served by each agricultural machine, and the waiting area visited by each agricultural machine is divided.

(3) Given that the Cauchy distribution has the largest dispersion characteristics and easily generates a random number far from the origin, enhancing the ability of the algorithm to jump out of the local optimal solution is beneficial. The Cauchy variation is used to add disturbance terms near the current optimal individual to expand the Cauchy distribution range and enhance the algorithm to jump out of the current local optimal. To this end, the following improvements are made:

$$X_{best,j}^{t+1} = X_{best,j}^{t} + \left(X_{best,j}^{t} - X_{i,j}^{t}\right) \times Cauchy\,(r,0,1) \quad (6)$$

At this time, when an individual is trapped in a local optimal, the use of Cauchy operator to generate a large step length can enhance the ability of the algorithm to jump out of the local optimal, and the Cauchy operator is used to generate a small step length to improve the optimization speed of the algorithm. $Cauchy\,(r,0,1) = 1/\pi \times (1/(r^2+1))$ is the standard Cauchy distribution, and r is the random number in $(0,1)$. Student i is a student randomly selected from the class, and $X_{i,j}^{t}$ is the exam result of student i in subject j (the tth exam). Formula (6) indicates that the best students work harder on the original basis and strive to continue to be the best students in the class.

3.2.3 Improved SPBO operator design

Three kinds of evolution operators, strong perturbation, weak perturbation, and learning strategy, are introduced, and the best students, good students, and poor students are evolved many times so that individuals cover the whole decision space. If the individual is the best student, the strong perturbation operation is used to adjust itself. The strong perturbation operator is an operation that greatly adjusts the individual, which is mainly used to explore the solution space and increase the ability of the algorithm to jump out of the local optimal solution. By randomly selecting two nodes and exchanging positions, the solution structure of the individual can be considerably changed, and a wide solution space can be quickly explored. This large-scale disturbance can break the local structure of the current solution and prevent individuals from falling into local optimal solution prematurely. It is specifically expressed as follows: Generate a random integer between 1 and D as I, and exchange the position of node [J] and node [I] to generate a new entity. If the individual is a good student, the weak disturbance operation is used to adjust itself. The weak perturbation operator is an operation that adjusts individuals in a small range, which is mainly used for fine optimization of local search and settlement. By optimizing the local structure of the current solution through the reverse node sequence, a better solution close to the current solution can be found. Compared with strong perturbation, the adjustment amplitude of weak perturbation is smaller, and the basic structure of high-quality solutions is not easy to destroy; thus, it is suitable for fine search. It is specifically expressed as follows: Generate random integers between 1 and D as I, reverse the sequence between node [J] and node [I], and generate new individuals.

If the individual is a poor student, then the learning operation with the best individual adjusts itself. The learning strategy operator adjusts the current individual to improve its quality by learning from the solution structure of the optimal individual. By using the structural information of the optimal individual (such as the arrangement order of adjacent nodes), it helps the individual learn the characteristics of the high-quality solution, accelerates the whole group to get closer to the global optimal solution, and thus improves the convergence speed and the quality of the algorithm. Specifically, the elements on the left and right sides of node G1 in the optimal individual are selected, and the elements on the right are denoted as G2. The locations where elements G1 and G2 are found in the individual to be evolved are denoted as I and J, and then the sequence between node [I+1] and node [J] is reversed to produce a new individual.

The combination of the three can effectively balance the contradiction between global exploration and local development, avoid premature convergence to the local optimal solution, and accelerate the search for the global optimal solution.The concrete implementation steps of improving the SPBO algorithm are as follows:

Step 1: Form the initial agricultural machinery scheduling scheme.

Step 2: When the order task appears, determine the information of the agricultural machinery to be executed in the cooperative for wheat harvesting, and establish a collection of unserved customer points w.

Step 3: Greey order insertion operation: Insert orders into the unserved harvest point set w in order in principle, calculate the cost increment of all the pluggable locations that meet the constraints, and take the minimum cost increment as the current optimal solution. The conditions for judging whether the new wheat waiting point is pluggable are as follows:

$$T_W \le MLT_W \tag{7}$$

$$T_{Wj} = T_W + S_i + t_{wk} \tag{8}$$

$$q_i \le Q \tag{9}$$

where represents the moment when the agricultural machine begins to serve the wheat harvesting point w, represents the latest time window of wheat harvest point w, represents the moment when the delivery vehicle starts serving wheat harvest point j after insertion of wheat harvest point w, indicates the time that the current wheat harvest point w needs to be served, denotes the travel time between wheat harvest points w and j.

Step 4: Remove order Worst, iterate through all orders in S, record the change of objective function value before and after removing order i from S, select q orders with the largest change to remove, and the removal cost formula is as follows:

$$\mathrm{Cos}t(i,S) = f(S) - f_{-i}(S) \tag{10}$$

where is the target value after removing order i from solution S.

Step 5: During the execution, if the judgment conditions of Step4 are not met, another agricultural machine is transferred to complete the wheat harvesting task.

Step 6: Until all new orders are inserted, use the path optimization algorithm to optimize the organization and end the scheduling.

4. Result Analysis and Discussion

4.1 Description of test data

The North China Plain is the main wheat growing area in China. Studies have shown that starting from May every year, the North China Plain and other places are the main export areas for the cross-regional operations of wheat combine harvesters, whose cross-regional operations range from tens of kilometers to hundreds of kilometers. In the numerical experiment, a farmland in Shandong Province (latitude 36°39'–36°55' N, longitude 115°27'–116°02' E) was analyzed. A total of 30 wheat harvesting points in the area were selected, and the plots were divided into 30 farmland operation points for simulation experiments. The distribution of each farmland operation point is shown in Figure 1. In accordance with the actual investigation and the collected experimental data, the model is analyzed by example.

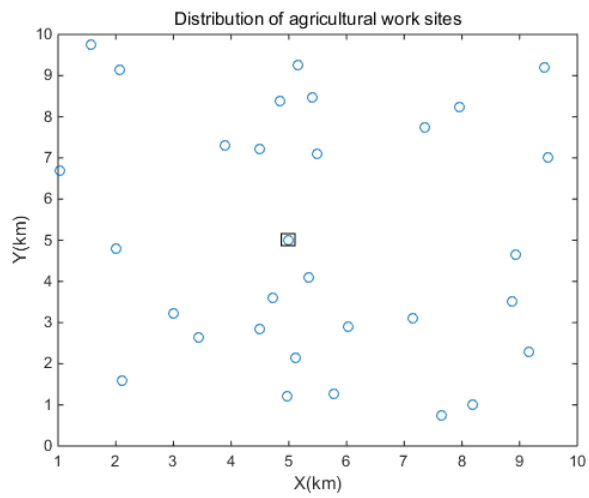

Fig. 1. Distribution of farmland operation points

The information of farmland operation points is shown in Table 1, where serial number T0 indicates the location of agricultural machinery cooperatives (5 km, 5 km), and serial number T1–T30 indicates farmland operation points.

4.2 Selection of experimental parameters

The following assumptions are made on the test data:

(1) This region has agricultural machinery cooperative, in which k agricultural machineries have the same operating efficiency of 0.4 km^2/h.

(2) The transfer speed of agricultural machinery is the same, i.e., 40 km/h, the transfer cost on the road is 2 yuan/km, the waiting cost of arriving in advance is 36

yuan/h, and the operating cost of agricultural machinery working in the operation point is 400 yuan/hm2.

(3) During the simulation, the working time of agricultural machinery was assumed to be 12 h every day.

(4) The agricultural machinery does not need to return to the agricultural machinery cooperative after the completion of the day's work and waits for the second day of work in the field to help the machinery perform the second day of work tasks.

(5) The agricultural machine returns to the starting point after completing all operations on the path. Table 2 shows the performance parameters and related operating costs of agricultural machinery.

Table 1. Information of farmland operation points

Encoding	Coordinate x (km)	Coordinate y (km)	Expected time window (h)		Area (mu)	encoding	Coordinate x(km)	Coordinate y(km)	Expected time window (h)		Area (mu)
T1	2.107	1.579	19	21	4.373	T16	9.482	7.01	20	22	3.829
T2	4.725	3.607	8	10	4.989	T17	3.004	3.236	17	19	4.815
T3	4.842	8.373	24	2	3.183	T18	8.876	3.517	7	9	3.449
T4	5.343	4.083	9	11	2.956	T19	7.638	0.733	16	18	2.622
T5	5.111	2.133	10	12	3.034	T20	7.153	3.112	11	13	2.775
T6	2.062	9.141	8	10	2.041	T21	5.154	9.245	22	24	2.474
T7	8.179	1.007	18	20	1.55	T22	9.15	2.281	18	20	2.23
T8	5.488	7.093	5	7	1.375	T23	5.789	1.267	13	15	3.256
T9	4.491	2.855	13	15	2.493	T24	9.432	9.206	20	22	1.125
T10	1.564	9.76	15	17	1.123	T25	3.902	7.31	4	6	2.298
T11	6.023	2.89	0	2	3.897	T26	4.973	1.206	6	8	1.591
T12	7.965	8.247	1	3	2.128	T27	3.438	2.624	12	14	4.341
T13	8.935	4.646	19	21	3.518	T28	7.355	7.731	23	1	4.045
T14	2.004	4.803	3	5	1.682	T29	4.501	7.206	16	18	4.411
T15	1.037	6.687	15	17	3.128	T30	5.411	8.464	2	4	4.702

Table 2. Technical parameters of the Zoomlion TK100PRO harvester

Item	Unit	Content
Engine power	KW	140
Overall dimensions (L × W × H)	mm	6400 * 3110 * 3450
Overall quality	kg	6500
Feed amount	kg/s	10
Working width	mm	2750
Minimum ground clearance	mm	300
Operating speed	km/h	0 to 10
Fuel consumption per unit area	kg/k ㎡	35 or less
Method of discharging grain	/	Mechanical automatic unloading
Cutting table auger type	/	Screw push type
Cutter type	/	Normal type II
Plucking wheel type	/	Eccentric spring gear type
Reel diameter	mm	1000
Number of wheel plates	unit	5
Main threshing drum type	/	Longitudinal axial flow
Main threshing drum size (outer diameter × length)	mm	Phi 700 × 2550
Gravure screen type	/	Grid type
Recovery mode	/	Volute + Auger type
Variable speed mechanism type	/	Mechanical + hydrostatic
Driving mode	/	two-drive
Drive type (front/rear)	/	Front: hydraulic drive, rear: none
Wheelbase	mm	2675
Guide wheel gauge	mm	1850
Drive wheel base	mm	1910

4.3 Result analysis

MATLAB2014a software was used to test the improved SPBO algorithm. The initial parameters were set as follows: population size, 100; maximum number of evolutionary iterations, 100; crossover probability, 0.9; and coefficient of variation, 0.5. The improved SPBO algorithm was used to analyze and calculate the example. The convergence curve of the improved SPBO algorithm is shown in Figure 2, and the optimal operation path of each agricultural machine in the last operation result was drawn, as shown in Figure 3.

The number "T0" represents the agricultural machinery cooperative, and the number "T1–T30" represents the field operation point. The number of agricultural machineries used is 5, and five optimal operation paths are obtained, and the vehicle transfer distance is 122.437 km. The improved SPBO algorithm was used to solve the model, and the optimal operation paths of agricultural machinery were obtained, as shown in Table 3.

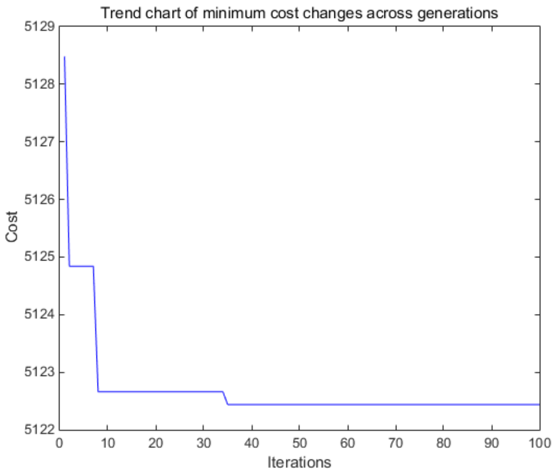

Fig. 2. Algorithm convergence curve

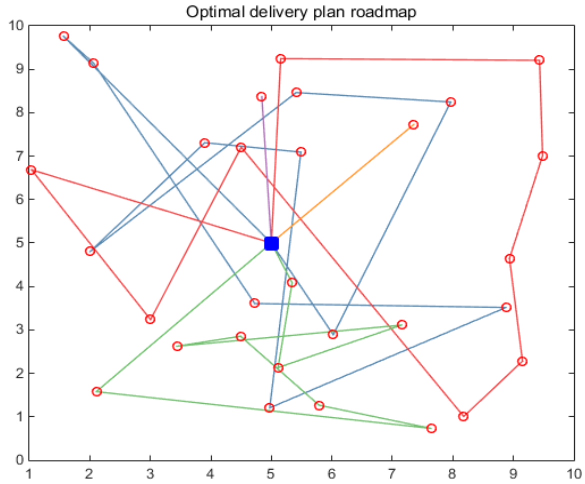

Fig. 3. Optimum operation path of agricultural machinery

Table 3. Optimal operation path of agricultural machiner

Agricultural machinery	Agricultural machinery operation path
Farm Machine 1	T0→T11→T12→T30→T14→T25→T8→T26→T18→T2→T6→T10→T0
Farm Machine 2	T0→T15→T17→T29→T7→T22→T13→T16→T24→T21→T0
Farm Machine 3	T0→T4→T5→T20→T27→T9→T23→T19→T1→T0
Farm Machine 4	T0→T28→T0
Farm Machine 5	T0→T3→T0

4.4 Algorithm effectiveness analysis

The above examples were tested and verified under the same experimental conditions, and the traditional SPBO algorithm was designed to conduct simulation experiments to verify the effectiveness of the improved SPBO algorithm proposed in this study. The convergence curve of the traditional SPBO algorithm is shown in Figure 4, and the optimal operation path of each agricultural machine in the last operation result is drawn, as shown in Figure 5. According to the traditional SPBO algorithm, the number of agricultural machineries used was 7, and seven optimal working paths were obtained, and the vehicle transfer distance was 131.895 km.

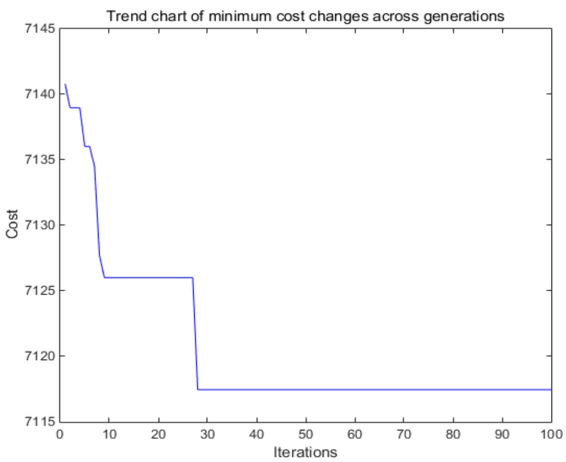

Fig. 4. Algorithm convergence curve

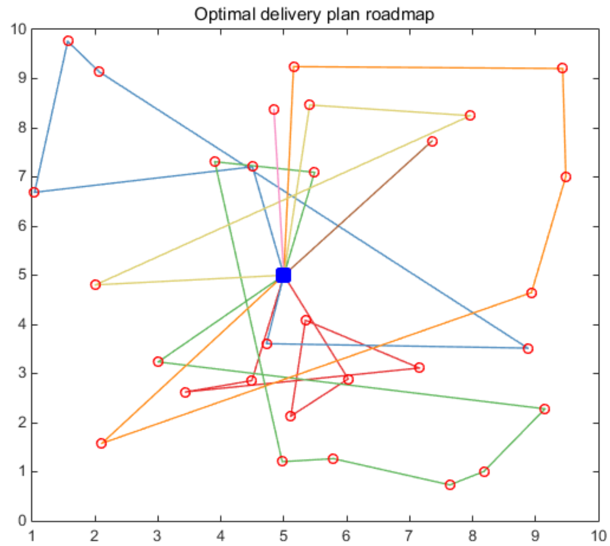

Fig. 5. Optimum operation path of agricultural machinery

The traditional SPBO algorithm was used to solve the model, and the optimal operation path of agricultural machinery was obtained, as shown in Table 4.

Table 4. Optimal operation path of agricultural machinery

Agricultural machinery	Agricultural machinery operation path
Farm Machine 1	T0→T11→T5→T4→T20→T27→T9→T0
Farm Machine 2	T0→T2→T18→T6→T10→T15→T29→T0
Farm Machine 3	T0→T8→T25→T26→T23→T19→T7→T22→T17→T0
Farm Machine 4	T0→T1→T13→T16→T24→T21→T0
Farm Machine 5	T0→T30→T12→T14→T0
Farm Machine 6	T0→T28→T0
Farm Machine 7	T0→T3→T0

The simulation results of the improved SPBO algorithm and traditional SPBO algorithm were compared and analyzed. The results showed that the target value based on the improved SPBO algorithm can save 14.29% compared with the traditional SPBO algorithm. In terms of running time, the improved SPBO algorithm is slightly higher than the traditional SPBO algorithm because the perturbation operation applied to the individual in the improved SPBO inevitably increases the time complexity of the algorithm. In terms of the number of agricultural machines enabled, the improved SPBO algorithm enabled five agricultural machines, while the traditional SPBO algorithm enabled seven agricultural machines. The improved SPBO algorithm is better than the traditional SPBO algorithm in terms of solving the complex problem of agricultural machinery scheduling with time window, proving that the decoding method used in this study has excellent performance in the early stage of iteration. From the perspective of the improved convergence curve of SPBO algorithm, its optimization ability is better, and it can jump out of the local optimal solution in time to improve the stability and robustness of the overall optimization.

5. Conclusions

An optimized mathematical model with time window was designed to solve the inter-regional agricultural machinery cooperative job scheduling problem, and an improved SPBO algorithm was proposed to solve the model. With the lowest total cost of agricultural machinery scheduling taken as the objective function, the cross-region scheduling problem of agricultural machinery was solved, and an improved solution was obtained under the premise of satisfying each field operation time window, which provided a more reasonable and efficient solution for agricultural machinery cooperatives to dispatch agricultural machinery. The improved SPBO algorithm and traditional SPBO algorithm were used to test 30 farmlands in Shandong Province. On the basis of the shortcomings of the standard SPBO algorithm, an individual decoding and repair strategy was proposed to improve the quality of the initial population. Three evolutionary operators, strong disturbance, weak disturbance, and learning strategy, were introduced to ensure population diversity and effectively avoid population prematurity and local optimization. The pairwise exchange strategy was used to renew the population and strengthen the local search ability. Finally, the reoptimization strategy was adopted to combine the worst removal of the order with the greedy insertion mechanism to solve the optimization problem of agricultural machinery scheduling path. Results show that the improved SPBO algorithm proposed in this study is superior to the traditional SPBO algorithm in terms of operation efficiency, total scheduling cost, and the number of agricultural machines used, and the cost savings of the improved SPBO algorithm is 14.29% compared with the traditional algorithm. At the same time, the improved SPBO algorithm has a better convergence effect, can stably and efficiently obtain the optimal path, and maximize the utilization of agricultural machinery resources, thus reducing the cost of agricultural machinery scheduling and greatly improving the overall efficiency and response ability of agricultural machinery scheduling systems. In follow-up research, how to make the algorithm avoid falling into the local optimal solution remains a problem to be solved.

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