

Retraction

Retracted: Optimization of Agricultural Machinery Task Scheduling Algorithm Based on Multiobjective Optimization

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] L. Zheng, "Optimization of Agricultural Machinery Task Scheduling Algorithm Based on Multiobjective Optimization," *Journal of Sensors*, vol. 2022, Article ID 5800332, 12 pages, 2022.

Research Article

Optimization of Agricultural Machinery Task Scheduling Algorithm Based on Multiobjective Optimization

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In order to improve the effect of agricultural machinery task scheduling, this paper starts from the perspective of multiobjective optimization to achieve task scheduling based on multiobjective particle swarm optimization algorithm. The position of each particle is a combination of resource options for each construction activity, and the displacement range and speed range of the particles are determined. Moreover, this paper uses the method of introducing an external storage library to store the current noninferior solutions and uses the adaptive grid method and the roulette selection method to select the global optimal solution of the particles. In addition, this paper proposes a task scheduling algorithm suitable for modern agricultural machinery based on the actual needs of current agricultural machinery task scheduling. The experimental results show that the agricultural machinery task scheduling algorithm based on multiobjective optimization proposed in this paper has a good agricultural machinery task scheduling effect and meets the basic purpose of optimizing the algorithm in this paper.

1. Introduction

With the development of the times, farmers' demand for agricultural machinery has become more and more urgent, and organizations such as agricultural cooperatives have gradually emerged. However, with the rapid development of agricultural mechanization, many problems have gradually emerged, which restrict the rapid development of agricultural mechanization. First, traditional agricultural production does not have a sound management system and lacks a reasonable number of management personnel, and agricultural production personnel are not strong in technical ability, have insufficient knowledge of agricultural machinery, and have weak maintenance capabilities. Second, due to the constraints of geographical location and economic level, some areas cannot increase investment in agricultural machinery, which largely restricts the development of regional agricultural mechanization. Third, with the development of agricultural mechanization, the increasing investment in agricultural machinery, and the expansion of management scale, the problems of lagging agricultural management informatization, poor timeliness, and low

information utilization have emerged. Moreover, it is difficult for managers to obtain agricultural machinery operation information and operating conditions in a timely and accurate manner, and they cannot reasonably schedule and allocate agricultural machinery [1].

With the further development of science and technology, Geographic Information System (GIS), Communication Packet Radio Service (GPRS), and Global Positioning System (GPS) have made considerable progress. Remote monitoring and management systems using 3S (GIS, GPRS, and GPS) and other key technologies have been widely used in transportation, logistics, and other fields. The application of these technologies also provides effective means for agricultural machinery information supervision services. A complete agricultural supervision system is composed of computer hardware and software, and it has functions such as automatic data collection, automatic monitoring, and business processing and integrates 3S technology and network technology to realize the system of remote collection and real-time monitoring of agricultural resources [2]. With the rise of land transfer policies, farmers have formed large-scale management entities by transferring land contractual management rights.

Moreover, the vast majority of farmers continue to explore in actual production, which promotes the formation of agricultural machinery service organizations and the emergence of agricultural machinery social services [3].

Agricultural machinery socialization services connect limited agricultural machinery with scattered farmers. Farmers no longer face huge purchase pressure and do not need to bear the high cost of operation and maintenance of agricultural machinery. On the other hand, it also improves the utilization rate of agricultural machinery resources. The agricultural machinery service organization is the carrier of the socialized agricultural machinery service. It has gone through multiple stages of development: agricultural machinery giants, agricultural machinery associations, agricultural machinery joint-stock cooperative organizations, and intermediary service organizations. Over the years, the forms of socialized agricultural machinery services have also continued to innovate, from organic households' mutual assistance to farming, to joint household operations, to joint-stock cooperative operations and cross-regional operations, fundamentally solve the problems of large-scale operation of agricultural machinery and small-scale production of hundreds of millions of farmers. The socialization of agricultural machinery services includes agricultural machinery service providers and demanders. Agricultural machinery service providers include agricultural machinery cooperative organizations and agricultural production operation contracting companies. They purchase agricultural machinery of different types of operations on a large scale to provide agricultural machinery demanders. Agricultural machinery operation services, agricultural machinery service demanders, such as contracted land managers and individual farmers, buying agricultural machinery by themselves is neither realistic nor economical, but there is an urgent need for agricultural machinery operations. The agricultural machinery service demand side publishes its own operation requirements, including constraints on the operation site, operation type, and operation time. The agricultural machinery service provides a large number of operation requirements, combined with the existing agricultural machinery resources, and requires the allocation of each farmland operation appropriate agricultural machinery and planning an appropriate driving route for each agricultural machinery, so as to maximize the use of resources. This new agricultural machinery operation mode has derived a new research topic, that is, the agricultural machinery scheduling problem studied in this article.

Based on the above analysis, this paper applies the multi-objective optimization research algorithm to agricultural machinery task scheduling and proposes a task scheduling algorithm suitable for modern agricultural machinery to improve the efficiency of agricultural machinery task scheduling and improve agricultural machinery management efficiency and agricultural machinery production efficiency.

2. Related Work

Reasonably plan the time for a variety of agricultural production operations. In this process, the available time, labor,

agricultural machinery resources, operation priority, and crop conditions are considered as important factors. Literature [4] proposes that there are two basic scheduling problems in the field of agricultural production: the first is a pure scheduling problem. For each job, the start time and end time of the job need to be determined in advance; the second is that the continuous scheduling problem requires that the resources shared by multiple jobs need to be organized in an orderly manner. He also first proposed a scientific method to solve scheduling problems in the agricultural field, which was mainly based on linear programming and simulation. Early methods could only solve pure scheduling problems. Literature [5] applies typical scheduling problems in the industrial field (such as job shop scheduling problems and flow shop scheduling problems) to continuous scheduling of agricultural field operations. Literature [6] proposes a special operation method for the VRP problem in the agricultural field to solve the planning and scheduling problems of field operations and has achieved good results in the scheduling of various types of agricultural operations. Literature [7] established a complete set of mathematical models for agricultural machinery continuous operation scheduling. The model includes input, data preprocessing, scheduling, and output. The output results include the agricultural machinery operation Gantt chart and the estimated cost of the scheduling plan. Solve the problem of continuous operation scheduling of agricultural machinery. Literature [8] combines neural network (NN) and genetic algorithm (GA) to optimize the path of agricultural robots. Through the high learning ability of NN, it can recognize the movement of the complex agricultural robot nonlinear system. The literature [9] improved the BRUSPLAN model based on the idea of integer planning for the planting of vegetable crops and established a two-stage stochastic linear programming (stochastic linear programming) model. Literature [10] established a linear programming model for rapeseed harvesting operations. The model considered resource constraints and operating time constraints and proposed two heuristic algorithms to solve the problem. The first method takes the operating rate as the primary optimization objective. The two methods meet the time window requirements as much as possible and optimize the starting time of each job. Literature [11] uses greedy algorithm and tabu search algorithm to optimize the scheduling path of agricultural machinery. The scheduling model takes into account the time lag caused by factors such as limited equipment and staff. The solution method of commercial integer programming software is adopted to solve a feasible scheduling plan within a reasonable calculation time. Literature [12] divides the agricultural machinery scheduling process into four independent steps: agricultural machinery allocation, farmland area coverage, agricultural machinery scheduling path generation, and secondary adjustment of the scheduling plan. Literature [13] studied the minimization of nonoperating mileage (that is, the transfer distance, excluding the mileage during internal operations of farmland) in the process of agricultural machinery scheduling. Regarding the problem as a binary integer programming problem, the path is optimized by calculating the traversal

sequence of parallel paths. Experiments show that the best traversal sequence is the optimal solution for minimizing nonoperating mileage.

Literature [14] proposed a two-stage metaheuristic algorithm combining simulated annealing algorithm and genetic algorithm and hybrid Petri network model to optimize the allocation and scheduling of agricultural machinery resources. In the first stage, the simulated annealing algorithm is used to optimize the resource allocation plan; in the second stage, the genetic algorithm is used to determine the priority of the job and generate the agricultural machinery scheduling plan according to the hybrid Petri network model. Literature [15] conducts detailed research and classification of agricultural machinery operation scheduling in order to abstract the common characteristics of different operation scenarios, establish a connection with traditional vehicle scheduling problems, and distinguish between agricultural machinery scheduling problems and vehicle scheduling problems with time windows. Literature [16] studied the dynamic agricultural machinery scheduling problem containing uncertain factors and proposed an abstract two-dimensional grid to create discrete transition nodes in the grid state space. Use the graph search algorithm to generate the optimal path. This algorithm improves the operation efficiency of agricultural machinery, and the calculation efficiency of the algorithm is high. It is suitable for multiple types of agricultural machinery to participate in the large-scale dynamic agricultural machinery scheduling problem at the same time.

3. Task Scheduling Algorithm Based on Multiobjective Optimization

The velocity update formula of the single-objective particle swarm optimization algorithm is shown in Equation (1), and the position update formula is shown in Equation (2). The optimal solution satisfying the termination condition is obtained through continuous iterations.

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1(p_i(t) - x_i(t)) + c_2 \cdot r_2(p_g(t) - x_i(t)), \quad (1)$$

$$x_i(t+1) = x_i(t) + v_i(t+1). \quad (2)$$

In the formula, $i = 1, 2, 3, \dots, I$. I is the total number of particles in the particle population; $t = 1, 2, 3, \dots, T$. T is the limit number of iterations; $v_i(t)$ is the velocity of the (i) particle at the (t)-th iteration; $x_i(t)$ is the position of the (i) particle at the (t)th iteration; $p_i(t)$ is the individual historical optimal solution of the pbest particle; $p_g(t)$ is the global optimal solution of the gbest particle; w is the inertia weight, which is nonnegative and is used to control the effect of the previous velocity on the current velocity; r_1 and r_2 are two random numbers, taking values in the range $[0, 1]$; c_1 and c_2 are acceleration constants, that is, learning factors.

Since the optimization objective of this paper is to trade-off the duration of agricultural machinery operations, the cost of agricultural machinery operations, and the quality

of agricultural machinery operations, achieving this optimization search process requires the use of a multiobjective particle swarm optimization algorithm (MOPSO). In the multiobjective particle swarm optimization algorithm, (t) and $Rh(t)$ in Equation (3) are used instead of $pi(t)$ and $pg(t)$, respectively. The velocity update equation of the particle is shown in [17]

$$v_i(t+1) = w \cdot v_i(t) + c_1 \cdot r_1(P_i(t) - x_i(t)) + c_2 \cdot r_2(R_g(t) - x_i(t)). \quad (3)$$

In the formula, $p_i(t)$ is the individual historical optimal solution of the particle selected by the dominating relationship; $p_g(t)$ is the global optimal solution of the particles selected from the external storage library in t iterations.

Particle position and velocity have a range of values. After the particle initialization and update, the particle position and velocity values that are out of the range should be adjusted. Values smaller than the lower limit are changed to the lower limit, and values larger than the upper limit are changed to the upper limit. The inertia weight w is used to control the effect of the previous velocity on the current velocity. In this paper, a typical linear decreasing inertia weight is used, as shown in Equation (4). The inertia weight decreases linearly with the number of iterations, and the inertia weight is maximum at the beginning to explore larger regions and quickly locate the approximate location of the optimal solution; after which the inertia weight gradually decreases and fine local exploration begins. Two random numbers r_1 and r_2 are randomly taken in the range of $[0, 1]$ to increase the randomness of the search. The learning factors c_1 and c_2 are used to regulate the maximum step size of learning, and both are taken as 2 in this paper.

$$w(t) = w_{\max} - \frac{w_{\max} - w_{\min}}{t_{\max}} \times t. \quad (4)$$

In the formula, $w(t)$ is the value of inertia weight in t iterations. w_{\max} is the maximum value of inertia weight, which is set to 0.95 in this paper. w_{\min} is the minimum value of inertia weight, which is set to 0.4 in this paper, and t_{\max} is the maximum number of iterations [18].

To establish a multiobjective particle swarm optimization model, the following key issues need to be solved: one is how to choose the individual historical optimal solution of the particle; the other is how to choose the global optimal solution of the particle. Regarding the individual historical optimal solution of selecting particles and for multiobjective optimization problems, it is impossible to directly compare the pros and cons of the two solutions. We use the dominance relationship to select, that is, select the nondominated solution as the individual historical optimal solution based on the Pareto principle. If the dominance relationship between the two cannot be judged, it is selected at random. Regarding the selection of the global optimal solution of the particles, there are various solutions such as the elite set strategy, the niche mirror method, and the adaptive mesh density method. This paper adopts the method of

introducing an external storage library to determine the global optimal solution. The function of the external storage library is to store the current noninferior solutions and select the global optimal solution of the particles in it. The external repository consists of two parts: archive controller and grid. This method uses both the adaptive grid density method and the roulette method.

The role of the archive controller is to determine whether to add a solution to the grid of the external repository. After the particle swarm has selected the current new noninferior solution, the process of judging whether the solution NS (new solution) is stored in the external storage library is as follows. If the external repository is empty, the solution is stored. If solution S1 already exists in the external storage and S1 dominates NS, then solution S1 is still stored. If solution S1 already exists in the external storage and NS dominates S1, then solution NS is stored and solution S1 is removed. If solution S1 already exists in the external repository and NS and S1 have no dominance relationship, then the solutions NS and S1 are stored, that is, the dominated solution will not be stored in the external repository, as shown in Figure 1.

The role of the grid is to generate a Pareto solution set with uniform distribution. In this paper, the density of the particles in the noninferior solution set is determined according to the adaptive grid density, and the global optimal solution is selected according to the particle density information. The grid is actually an objective function space formed by multiple hypercubes (unit grids), and the dimension of the hypercube is consistent with the number of objective functions. Take the optimization problem in this paper as an example; the grid is a three-dimensional space, and the specific steps are as follows:

The first step is to determine the boundary of the grid. In the t -th iteration, the grid boundary is $(\min PT^t, \max PT^t)$, $(\min PC^t, \max PC^t)$, and $(\min PQ^t, \max PQ^t)$, and $\min PT^t$ and $\max PT^t$ are the smallest and largest calculated by the PT objective function of the particles that have been stored in the external storage library. The fitness value is the same for the rest.

The second step is to calculate the modulus length of each grid, as shown in Equation (5). The grid in this paper is the objective function space formed by $D \times D \times D$ hypercubes.

The third step is to calculate and determine the grid numbers of all particles stored in the external storage library, as shown in Equation (6) [19].

$$\begin{aligned} \Delta PT^t &= \frac{\max PT^t - \min PT^t}{D} \quad \Delta PC^t = \frac{\max PC^t - \min PC^t}{D} \quad \Delta PQ^t \\ &= \frac{\max PQ^t - \min PQ^t}{D}. \end{aligned} \quad (5)$$

In the formula, ΔPT^t is the modulus length of the grid in the direction of the objective function PT during t iterations. ΔPC^t is the modulus length of the grid in the direction of the objective function PC during t iterations. ΔPQ^t is the mod-

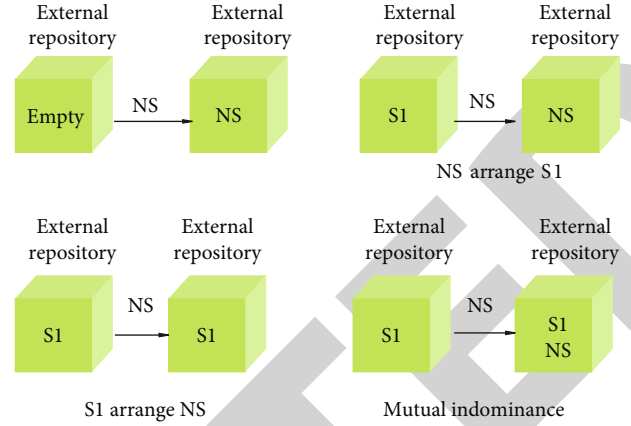


FIGURE 1: Schematic diagram of the role of the archive controller.

ulus length of the grid in the direction of the objective function PQ during t iterations. D is the divisor, which can determine the number of hypercubes (unit grids) in the grid, and the study by Coello and Lechuga suggests a value range of 30-50.

$$\text{Int} \left(\frac{PT_i^t - \min PT^t}{\Delta PT^t} \right) + 1 \text{Int} \left(\frac{PC_i^t - \min PC^t}{\Delta PC^t} \right) + 1 \text{Int} \left(\frac{PQ_i^t - \min PQ^t}{\Delta PQ^t} \right) + 1. \quad (6)$$

In the formula, PT_i^t is the fitness value calculated by the PT objective function of particle i in t iterations. Int is a function of rounding down.

The fourth step is to determine the number of particles in each grid, that is, the particle density. The fifth step uses the roulette selection method to select the global optimal solution.

In order to ensure the diversity of noninferior solution sets and explore more space, the lower the particle density in the grid, the greater the probability of being selected. Coello and Lechuga proposed to use 10 divided by the number of particles in the unit grid x_i as the fitness of the i -th unit grid $f(x_i)$ ($i = 1, 2, \dots, N$), and N is the number of unit grids that hold particles. The algorithm calculates the fitness ratio, that is, the ratio of the fitness of the i -th unit grid to the sum of all fitness, as shown in Equation (7). The algorithm calculates the cumulative probability q_i , that is, the sum of the fitness ratios from the first unit grid to the i -th unit grid, as shown in Equation (8). The algorithm randomly generates $r \in [0, 1]$. The algorithm starts from q_1 . If $q_1 > r$, the unit grid 1 is selected. If $q_1 < r$, then $i + 1$, and then, the algorithm judges q_2 until $q_i > r$, the unit grid i is selected. Then, the algorithm randomly generates $r \in [0, 1]$ again to judge from q_1 and makes a total of N selections. The algorithm determines the unit grid that has been selected the most times (the number may be greater than 1) and randomly selects a particle in the determined grid as the global optimal solution.

$$p(x_i) = \frac{f(x_i)}{\sum_{j=1}^N f(x_j)}. \quad (7)$$

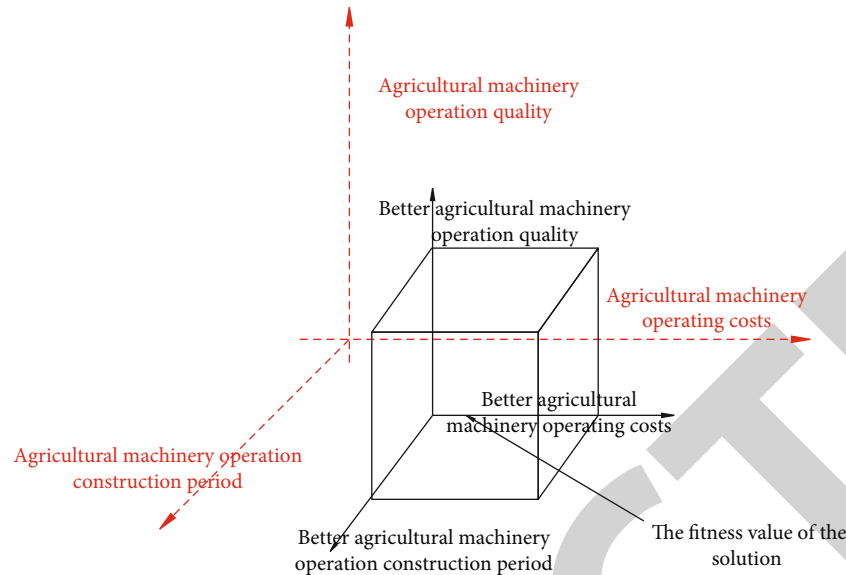


FIGURE 2: Schematic diagram of the optimization goal of agricultural machinery operation scheduling.

In the formula, $p(x_i)$ is the fitness ratio of the unit grid x_i and $f(x_i)$ is the fitness of the unit grid x_i .

$$q_i = \sum_{j=1}^i p(x_j). \quad (8)$$

In the formula, q_i is the cumulative probability of the unit grid x_i .

If the particles in the external storage library have reached the set maximum allowable capacity, it is necessary to remove the relatively low-quality solutions (particles). In order to ensure the uniformity and diversity of the noninferior solution set, the particles in the grid with higher density are removed. Particle removal only considers the unit grid with the number of particles greater than or equal to 2, which is expressed in the research of Yang Junjie and others, as shown in

$$CO_k = \text{Int} \left(\frac{|A_t| - L}{|A_t|} \times G_{k,2} \right) + 0.5. \quad (9)$$

In the formula, CO_k is the number of particles that need to be removed in the unit grid k . L is the maximum allowable capacity of the number of particles stored in the external storage library, which is artificially specified. $|A_t|$ is the number of particles in the external storage library at t iterations. $G_{k,2}$ is the number of particles in the unit grid k where the number of particles is greater than or equal to 2.

The optimization objective of this paper is to minimize the duration and cost of agricultural machinery operations while maximizing the quality performance of agricultural machinery operations, that is, to obtain a Pareto optimal solution that weighs duration-cost-quality of agricultural machinery operations.

The optimization model of agricultural machinery operation scheduling in this paper takes the resource options of

each agricultural machinery operation activity of the project as the decision variables, considers the priority constraints among agricultural machinery operation activities, and contains the following three objective functions, as shown in Equations (10), (11), and (12), to evaluate the duration of agricultural machinery operation, cost of agricultural machinery operation, and quality of agricultural machinery operation of the project, respectively. The objective functions are used to calculate the fitness values as a basis for meritocracy among particles, as shown in Figure 2.

The minimized agricultural machinery operation duration is

$$PT_{\min} = \sum_{i=1}^I T_{i,n}. \quad (10)$$

In the formula, i is the serial number of the agricultural machinery operation activity, $i = 1, 2, \dots, I$. n is the serial number of the resource option, $n = 1, 2, \dots, N$. $T_{i,n}$ is the agricultural machinery operation activity on the critical path (i) selection of resource options (n) continuous agricultural machinery operation duration.

Since the optimization model considers the priority constraints among agricultural machinery operation activities, the minimized agricultural machinery operation duration is the minimized critical path agricultural machinery operation duration, and the critical path is the route with the longest duration among agricultural machinery operation routes.

The minimized agricultural machinery operation cost is

$$PC_{\min} = \sum_{i=1}^I C_{i,n}. \quad (11)$$

In the formula, $C_{i,n}$ is the agricultural machinery

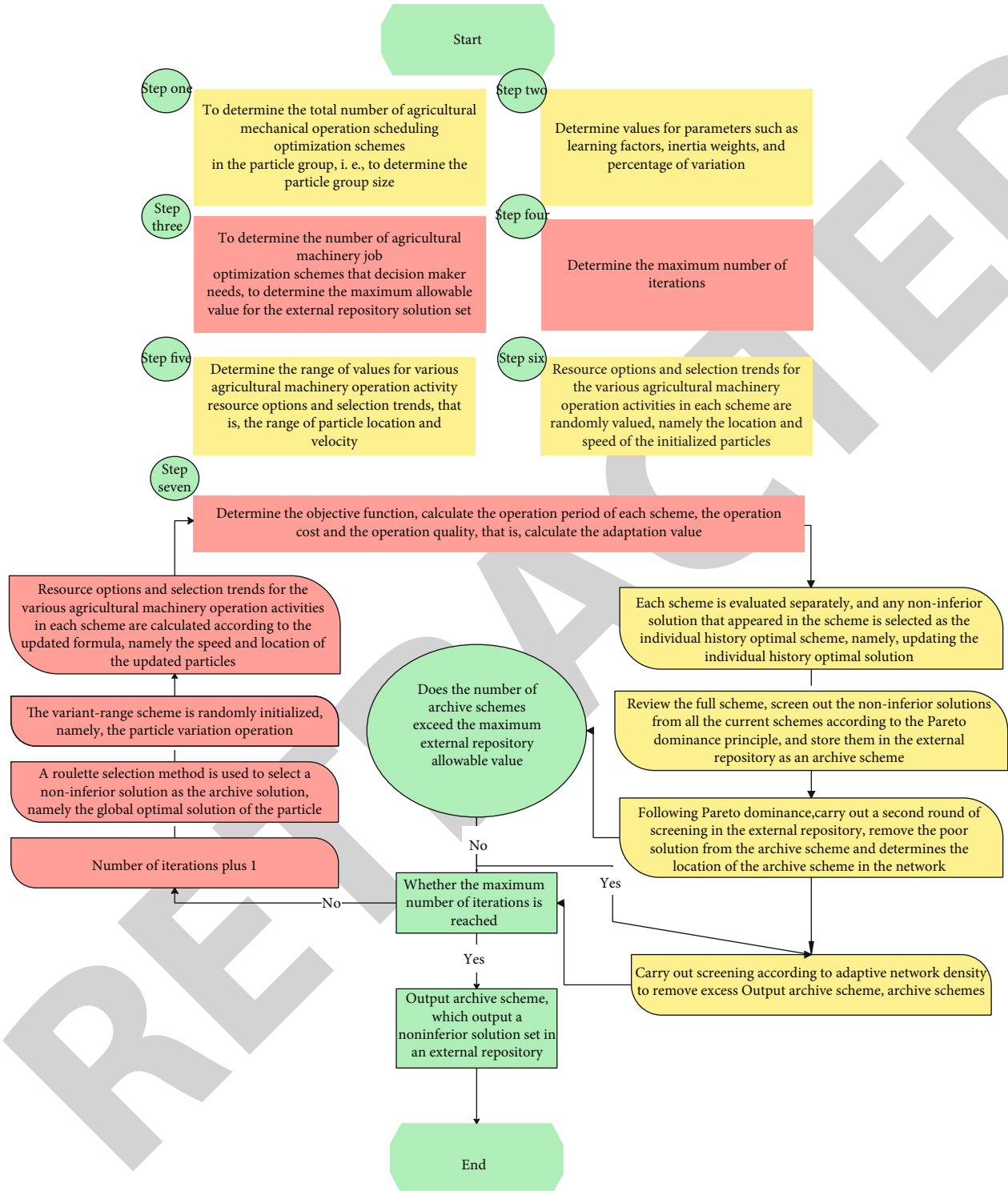


FIGURE 3: Flowchart of the MOPSO-CSO model.

operating cost consumed when the agricultural machinery operating activity (i) selects the resource option (n).

Due to the need to consider the individual costs of various agricultural machinery operations, the agricultural machinery operating costs in this paper are the direct construction costs of the project quota, that is, the sum of labor costs, material costs, and agricultural machinery operating

equipment. The agricultural machinery operating cost of this optimization model does not include enterprise management fees, general risk fees, profits, measurement fees, supervision fees, safe and civilized agricultural machinery operating fees, and taxes. In the case of constant rates, these costs do not affect the comparison of optimization plans, and decision-makers can schedule the final agricultural

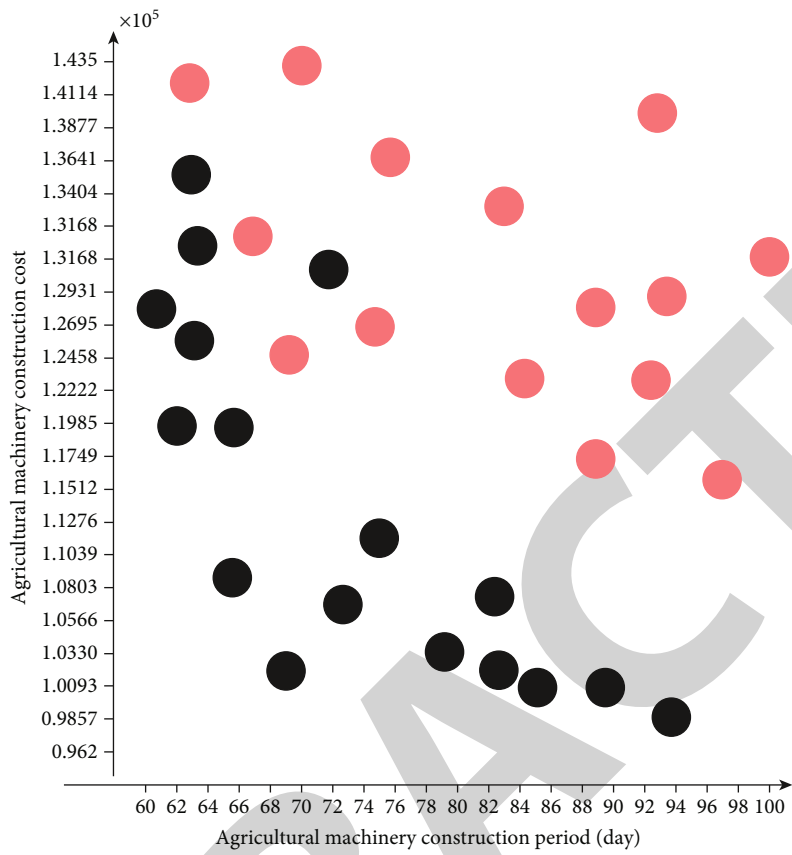


FIGURE 4: Optimization and iteration results of the MOPSO-CSO model.

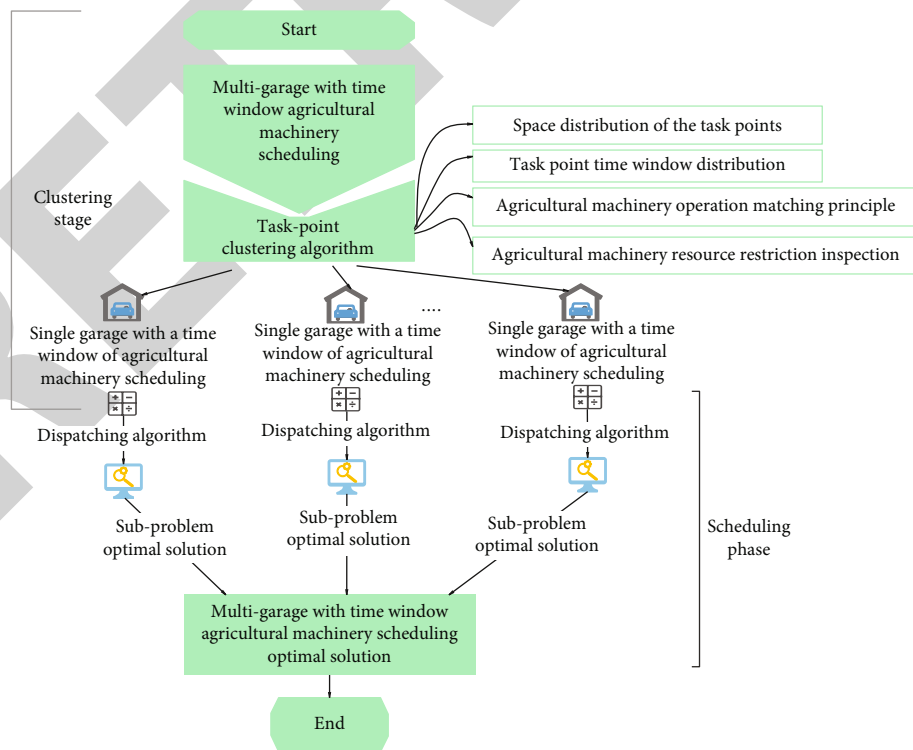


FIGURE 5: The basic framework of agricultural machinery task scheduling algorithm.

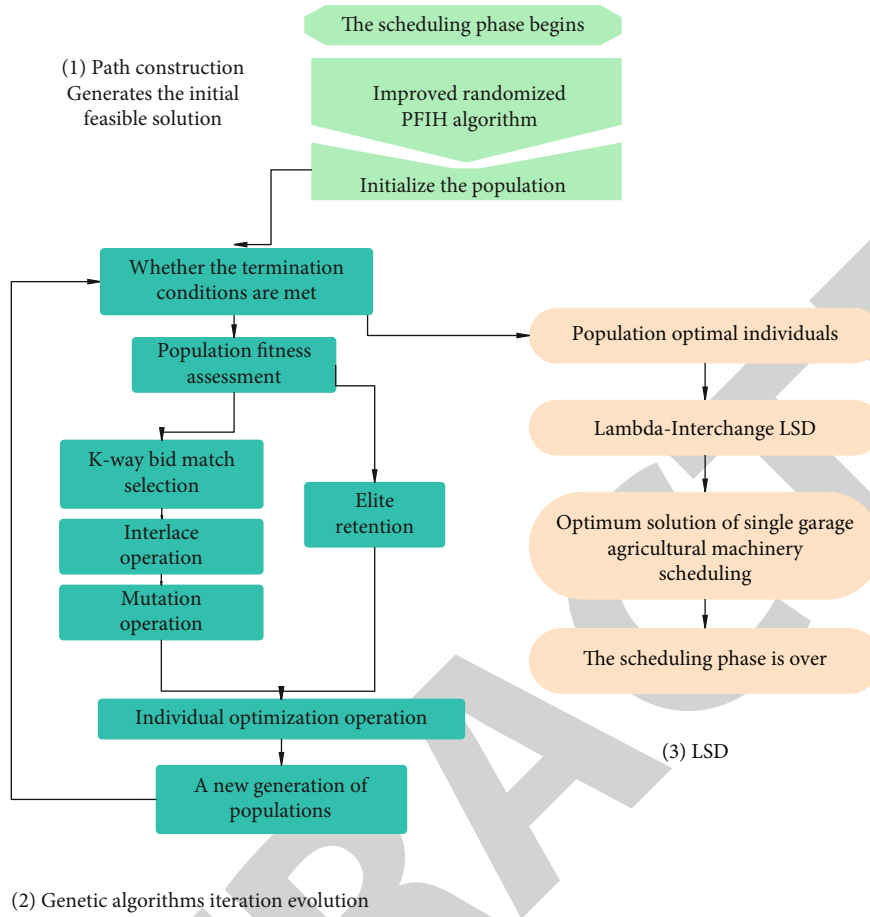


FIGURE 6: Algorithm flowchart of the scheduling stage.

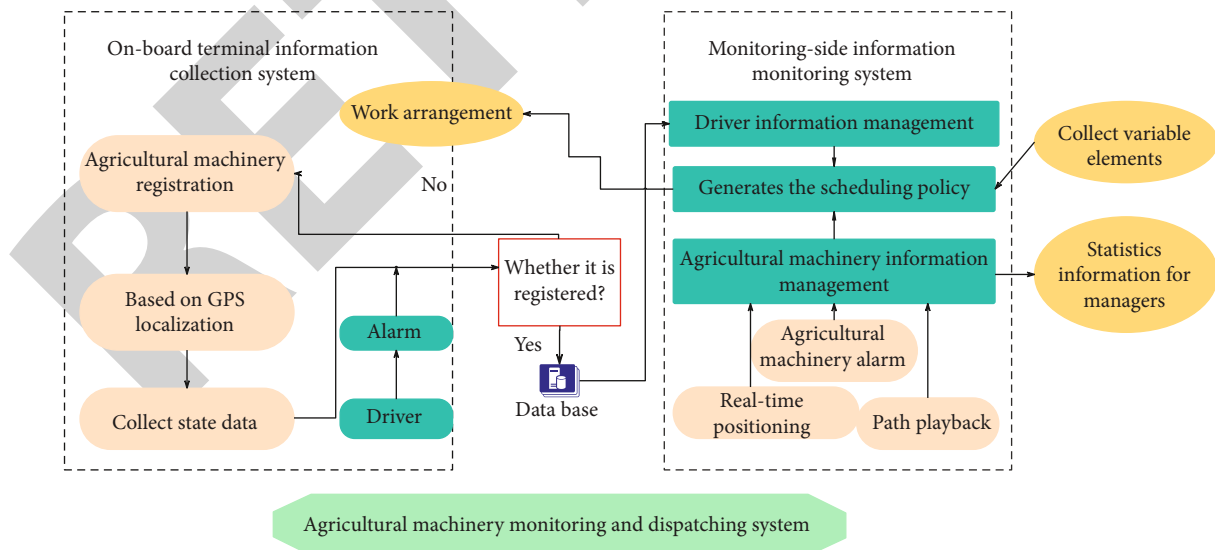


FIGURE 7: Agricultural machinery monitoring and dispatching system.

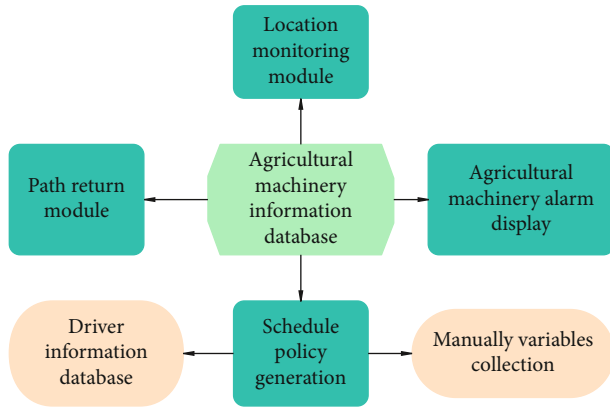


FIGURE 8: Data acquisition and display.

machinery operation plan. It calculates the standards of various companies in each region based on the resulting fixed direct project costs and different rates.

The maximized quality of agricultural machinery operations is

$$PQ_{\max} = \sum_{i=1}^I w_i * Q_{i,n}. \quad (12)$$

In the formula, $w_{i,n}$ is the weight of the agricultural machinery operation activity (i) in the overall quality performance of the project, and $Q_{i,n}$ is the agricultural machinery operation quality performance when the resource option (n) is selected for the agricultural machinery operation activity (i).

This model of agricultural machinery operation scheduling optimization (MOPSO-CSO) is developed. The model is implemented in such a way that each particle represents an agricultural machinery operation scheduling scheme (referred to as a scheme in the pseudocode and flowchart). The combination of resource options for each agricultural machinery operation activity in the agricultural machinery operation scheduling scheme is used as each particle position with integer values ranging from 1 to M_i ($i = 1, \dots, N$); M_i is the total number of resource options to be considered for agricultural machinery operation activity i . Thus, the range of particle positions is limited to $[1, M_i]$. Its corresponding next selection trend, that is, the particle velocity range, is limited to $[1 - M_i, M_i - 1]$. Furthermore, the values of each dimension of the initial and updated positions of the particles should be rounded to integers in $[1, M_i]$. The implementation process of the MOPSO-CSO model, that is, the pseudocode, is summarized as follows.

- (1) The algorithm determines the total number of agricultural machinery operation scheduling schemes in the particle swarm, that is, the algorithm determines the size of the particle swarm

- (2) The algorithm determines the value of the learning factor, inertia weight, and mutation operator and other parameters
- (3) The algorithm determines the upper limit of the number of agricultural machinery operation scheduling schemes that the decision-maker needs, that is, the algorithm determines the maximum allowable value of the solution set of the external storage library
- (4) The algorithm determines the maximum number of iterations
- (5) The algorithm determines the value range of the resource options and selection trends of various agricultural machinery operation activities, that is, the algorithm determines the value range of the particle position and velocity
- (6) The algorithm randomly initializes the resource options and selection trend values of each agricultural machinery operation activity in each scheme, that is, the algorithm initializes the position and velocity of the particles
- (7) The algorithm determines the objective function (Equations (10)–(12)). The algorithm calculates the agricultural machinery operation duration, agricultural machinery operating cost, and agricultural machinery operating quality of each scheme, that is, the algorithm calculates the fitness value
- (8) The algorithm evaluates each plan individually. According to the principle of Pareto dominance, the algorithm selects the best

The combination of resource options for agricultural machinery operation activities is taken as the individual historical optimal solution, that is, the algorithm updates the individual historical optimal solution.

- (9) Algorithmic evaluation of all schemes: according to the principle of Pareto dominance, the algorithm filters out the noninferior solutions in all current solutions and stores them in an external repository as archive solutions
- (10) According to the principle of Pareto dominance, the algorithm performs a second round of screening in the external repository to remove the inferior solutions in the archive plan
- (11) The algorithm judges whether the number of archive schemes exceeds the maximum allowable value of the external storage library. If it exceeds, the algorithm filters according to the adaptive grid density to remove redundant schemes. Otherwise, the algorithm proceeds to the next step
- (12) The algorithm judges whether the maximum number of iterations is reached or the solution set converges. If it exceeds, the algorithm goes to Step 16

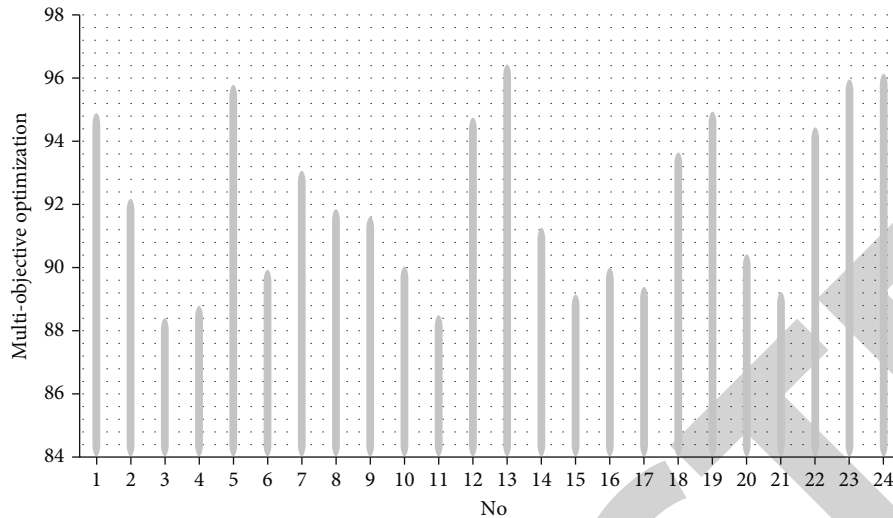


FIGURE 9: Multiobjective optimization effect.

to exit the loop; otherwise, the algorithm goes to the next step to loop

- (13) According to the adaptive grid density, the algorithm uses the roulette selection method to select the optimal combination of agricultural machinery operation resource options in the archive plan as the global optimal plan, that is, the global optimal solution of the particles
- (14) The algorithm initializes the schemes within the mutation range randomly, that is, the algorithm performs particle mutation operations
- (15) The algorithm calculates the resource options and selection trends of each agricultural machinery operation activity in each scheme according to the update formula of the multiobjective particle swarm optimization algorithm (Equations (2) and (3)), that is, the algorithm updates the speed and position of the particles, and the algorithm goes to Step 7 to continue to loop
- (16) The algorithm outputs archive scheme, that is, the algorithm outputs the noninferior solution set in the external storage library

Above, 1 to 6 are the initial stage, 7 to 15 are the cycle stage, and 16 is the end stage. The flowchart of the MOPSO-CSO model is shown in Figure 3.

The optimization iteration results of the MOPSO-CSO model in this paper are shown in Figure 4.

In Figure 4, the black particles represent the selected Pareto optimal solution, and the red particles represent the particles eliminated in the external storage during the iteration process. It can be seen that the particles gradually converge to the Pareto optimal solution. The position of the solution is evenly distributed, indicating that the model has a strong global search ability.

4. Agricultural Machinery Task Scheduling Algorithm Based on Multiobjective Optimization

The basic framework of agricultural machinery task scheduling algorithm is shown in Figure 5.

In the scheduling stage, a multiobjective algorithm is used to solve the agricultural machinery scheduling problem with time windows. The algorithm is divided into three steps. The first step uses an improved insertion path construction algorithm to generate an initial feasible solution to the problem. In the second step, multiple initial feasible solutions form the initial population. By designing suitable chromosome codes, fitness evaluation functions, genetic operators, etc., genetic algorithms are used to perform evolutionary operations such as selection, crossover, mutation, and individual optimization on the initial population. In the third step, after the evolution reaches the termination condition, the neighborhood search technology is used to further improve the optimal individual of the population and obtain a better solution. The algorithm flowchart of the scheduling phase is shown in Figure 6.

The location monitoring of agricultural machinery is conducive to the unified management of scattered agricultural machinery, coordinated deployment of agricultural machinery, and timely and accurate provision of the addresses of agricultural machinery that need to be repaired for maintenance personnel. Moreover, it provides idle agricultural machinery for the farmland that needs to be operated in time, prevents the resources of the agricultural machinery from being idle, saves time, and reduces costs. The system needs to facilitate the management of agricultural machinery information statistics and management, including agricultural machinery workload, working hours, repairs, location information, agricultural machinery model, license plate number, and fuel consumption. The operation status information of agricultural machinery is obtained in

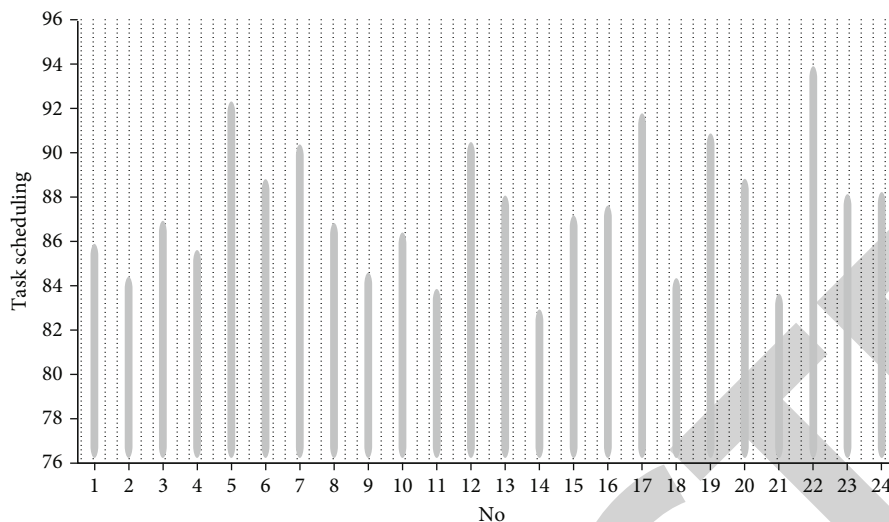


FIGURE 10: Task scheduling effect of agricultural machinery.

real time by the vehicle terminal and transmitted to the database of the monitoring system.

The monitoring terminal system automatically generates instructions for the optimal dispatch path or an emergency situation requires notification to the vehicle terminal. Moreover, it can interact (voice or text) with the in-vehicle App through text messages or directly through the communication network to inform the operator of the vehicle. The system uses MySQL database to store data. The system development idea is shown in Figure 7.

The relationship of the system data table is very simple. The agricultural machinery is successfully registered, and the agricultural machinery information database allows this agricultural machinery to upload data. The data in the agricultural machinery information database provides data support for agricultural machinery location monitoring, path playback and scheduling strategy generation, and alarm agricultural machinery display modules. The data relationship flowchart is shown in Figure 8.

In this paper, the performance verification of the multi-objective agricultural machinery task scheduling algorithm introduced in this paper is carried out. First, the multiobjective optimization effect of the algorithm in this paper is evaluated through simulation experiments, and the results shown in Figure 9 are obtained.

Through the above research, we can see that the algorithm proposed in this paper has certain advantages in multiobjective optimization. On this basis, this paper evaluates the effect of agricultural machinery task scheduling of agricultural machinery task scheduling algorithm based on the multiobjective optimization proposed in this paper and obtains the results shown in Figure 10.

From the above research, it can be seen that the agricultural machinery task scheduling algorithm based on multiobjective optimization proposed in this paper has a good agricultural machinery task scheduling effect and meets the basic purpose of optimizing the algorithm in this paper.

5. Conclusion

The research and development of a remote agricultural machinery monitoring service system integrating technology and management mode can realize remote monitoring, management, and mobilization of agricultural machinery and truly improve the efficiency of human and agricultural machinery and the level of agricultural information management. This paper designs an agricultural machinery operation and maintenance management system, which has the functions of agricultural machinery information management, agricultural machinery location monitoring, and communication scheduling. It is mainly aimed at agricultural machinery cooperatives and other agricultural machinery cooperative organizations and can conduct real-time and accurate monitoring and management of agricultural machinery at all levels across the country. At the same time, it also gives full play to the advantages of the development of mobile communication and the popularity of the development of mobile terminals, which effectively compensates for the disadvantages of poor flexibility and mobility of the traditional agricultural machinery monitoring and management end. In addition, it breaks through the constraints of agricultural machinery management in terms of time and space in the true sense and maximizes the efficiency of agricultural machinery production. This paper applies the multiobjective optimization research algorithm to agricultural machinery task scheduling and proposes an algorithm suitable for modern agricultural machinery task scheduling. The experimental results show that the multiobjective agricultural machinery task scheduling algorithm proposed in this paper has a good agricultural machinery task scheduling effect and meets the basic purpose of optimizing the algorithm in this paper.

Data Availability

The labeled dataset used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares no competing interests.

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