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AN IMPROVED MULTI-OBJECTIVE GREY WOLF OPTIMIZATION TASK ALLOCATION METHOD IN MOBILE CROWD SENSING FOR SMART AGRICULTURE

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Abstract:

Smart agriculture is the key to ensuring China's food and water resource security. However, the operation and maintenance efficiency of the irrigation canal network that spreads across farmlands is constrained by the traditional inefficient inspection methods. Mobile crowd sensing (MCS) offers a new approach for the inspection of farmland water channels. By mobilizing farmers' daily mobile resources, it is expected to achieve low-cost and wide-coverage monitoring. The core of its efficiency lies in the intelligent allocation of sensing tasks. However, most of the existing mobile crowd sensing methods are designed based on general scenarios and have not been fully adapted to the scene characteristics of farmland water channel detection, such as "numerous points, long lines, complex terrain, and hidden problems", making it difficult to effectively coordinate and optimize the two mutually restrictive core goals of platform benefits and total costs for farmers. To solve these problems, this paper proposed a multi-objective optimization task allocation model in mobile crowd sensing for the inspection of smart agricultural canals. In order to solve the proposed model, we designed an improved multi-objective grey wolf optimization algorithm (IMOGWO-SA/D) that integrates simulated annealing (SA) mechanism and decomposition strategy. This algorithm collaboratively optimizes multiple single-objective sub-problems through Chebyshev decomposition and enhances the global search ability with the aid of SA mechanism, thereby effectively balancing convergence and the distribution of solution sets. Through simulation experiments and comparisons with traditional benchmark algorithms, the experimental results show that the algorithm proposed in this paper has significant advantages in convergence, diversity of solution sets and scene

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adaptability. This article provides innovative methods and technical solutions for building an efficient and low-cost distributed monitoring system for smart agriculture.

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Keyword:

Canal Inspection, Grey Wolf Optimizer, Mobile Crowd Sensing; Multi-objective Optimization, Smart Agriculture, Task Allocation

Introduction

As a major agricultural country, China regards food and water security as the core of its national strategy. As the "capillaries" of agricultural water conservancy facilities, the integrity and smoothness of farmland irrigation canals directly affect the efficiency of water resource utilization and crop yields. However, in China, irrigation canals for farmland are widely distributed, long in route and complex in environment. The traditional method of relying on full-time water conservancy workers for regular inspections has prominent contradictions such as high labor costs, long inspection cycles and delayed problem discovery. Especially during the flood season or peak irrigation period, if local siltation, collapse or leakage of water channels are not detected and repaired in time, it may lead to large-scale farmland suffering from drought or flood, causing significant economic losses.

In recent years, the development of smart agricultural technology has provided new ideas for solving this difficult problem. Among numerous technical paths, mobile crowd sensing (MCS) stands out as a cutting-edge data acquisition model, providing a practical and feasible solution to this problem. MCS has significant advantages such as low cost, wide coverage and strong real-time performance by recruiting a large number of ordinary users to collaborate on large-scale and distributed sensing tasks using their portable smart devices (such as smart phones). The vast number of farmers work in the fields every day, and their activity trajectories naturally cover the key nodes of the water channel network, making them a potential and large-scale sensing group. If an effective mechanism can be designed to encourage farmers to use mobile phones to collect and report the key conditions of water channels (such as water level, flow rate, and images of channel damage) in their daily activities, a real-time and dynamic "neural network" for monitoring the health of water channels can be constructed, which is of great practical significance for improving the management level of agricultural infrastructure and reducing operation and maintenance costs.

However, applying MCS to the inspection of farmland water channels faces dual challenges: 1) multi-objective trade-off: The platform pursues efficiency and low cost, while farmer participants focus on the fairness of benefits and burdens. These demands are mutually restrictive under the condition of limited resources; 2) Spatio-temporal constraints: Sensing tasks must be completed at a specific time and location, while the movement trajectories of farmer participants are restricted by the patterns of agricultural activities. To effectively address these challenges, it is essentially necessary to solve the core issue of farmland water channel inspection - task allocation, that is, how to intelligently match inspection tasks to appropriate participants to optimize overall efficiency. The rationality of the sensing task allocation scheme will directly affect the overall completion quality of the task. Therefore, constructing an intelligent sensing task allocation model and method that fits the scene of farmland water channel inspection is the research focus of this paper.

In the field of task allocation for MCS, scholars at home and abroad have achieved a series of results. Early studies mostly focused on single-objective optimization, such as minimizing the energy consumption of sensing data transmission (Xiong et al., 2014) or maximizing the quality of sensing data (Wang et al., 2016). As application scenarios become more complex, the research focus has shifted to multi-objective optimization. Li et al. (2019) proposed a dual-objective optimization method that takes into account the maximization of overall quality utility under budget constraints and the minimization of overall incentive payment under a given quality utility and respectively designed the greedy algorithm and the Pareto optimal particle swarm optimization algorithm for solution. Shen et al. (2022) proposed a variable-speed multi-task allocation model, aiming to simultaneously maximize user rewards and minimize task completion time, and improve the fairness of task allocation by introducing an upper limit on the number of tasks associated with reputation. In recent years, research has shown a trend of deep intersection of algorithms and fine modeling of scenarios. For instance, Liu et al. (2025) aimed to enhance familiarity and satisfaction in periodic task allocation by integrating the simulated annealing (SA) strategy into game theory (GT) to optimize the update process. They designed a GT algorithm based on the SA strategy, ultimately achieving more effective matching results. Bouakline et al. (2024) addressed the issue of air quality prediction by integrating an improved genetic algorithm (GA) with a long short-term memory network (LSTM). They utilized GA to automatically optimize the hyperparameters and feature selection of LSTM, thereby enhancing the model's prediction accuracy. Also addressing the deployment issue of urban PM2.5 monitoring networks, Chang-Silva et al. (2024) utilized the NSGA-II algorithm for multi-objective optimization, ensuring monitoring accuracy while reducing the number of sensors and optimizing sensor location under resource-constrained conditions. In addition, Luo et al. (2025) proposed a multi-objective task allocation and pricing framework that integrates game modeling and deep reinforcement learning, significantly enhancing the intelligent decision-making ability and resource collaboration efficiency of the system.

However, most of the existing studies are applicable to smart city scenarios such as road traffic and environmental monitoring. The movement patterns of the recruited participants are significantly different from those in farmland scenarios. If the existing methods are directly applied to the farmland water channel inspection scenario, there will be a problem of insufficient applicability. Firstly, in terms of scene modeling, the existing methods fail to fully take into account the uniqueness of agricultural scenes. For instance, the movement patterns of

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participants (farmers) are restricted by agricultural laws, task points (canals) are distributed in a linear network pattern, and sensing data (such as images) are related to conditions such as shooting angles and lighting. Secondly, in terms of optimization objectives, there is a certain deviation between its core demands and the key goals that need to be comprehensively balanced in agricultural inspections, such as platform benefits and total costs for farmers.

In addition, there are still relatively few studies on the application of MCS in agriculture. Although a few studies have applied MCS to the monitoring of farmland pests and diseases, such as Sivagnanasundaram et al. (2019) which developed a prototype platform for the collection of agricultural pest and disease information, no multi-objective optimization model has been constructed for the trade-off between efficiency and cost in task execution. Nor have effective intelligent algorithms been designed to solve and support decision-making. Moreover, Coletta et al. (2020) proposed an optimized deployment scheme for crop disease diagnosis based on an MCS framework, which mainly addressed the issues of high equipment deployment costs and insufficient coverage in crop disease monitoring in developing countries. However, this study focused on static equipment deployment and basic task allocation and did not take into account the requirements of multi-objective optimization.

In view of the above problems, under the background of promoting smart agriculture in China, this paper aims to construct a multi-objective optimization model that accurately depicts the scene characteristics of farmland water channel inspection. Under the constraints of ensuring a high task completion rate and platform budget, with the dual optimization goals of maximizing platform benefits and minimizing the total cost for farmers, an improved multi-objective grey Wolf optimization algorithm (IMOGWO-SA/D) integrating simulated annealing mechanism and decomposition strategy is designed to solve the above model, ultimately achieving the intelligent allocation of inspection tasks.

The main contributions of this paper are as follows:

1) Firstly, this paper precisely depicts the core contradiction and optimization objective in the specific scenario of inspecting farmland water channels. Our model innovatively deconstructs this complex relationship into two levels (platform benefit level and participant cost level) and two dimensions of optimization objectives (maximizing the total platform revenue and minimizing the total cost for farmers), thereby constructing a more practical multi-objective optimization model. This model does not presuppose a unique optimal solution. Instead, it seeks a series of optimal Pareto solution sets for decision-makers to make flexible choices based on the actual situation. This enables the model to move from theory to practice and has strong application guidance value.

2) This paper proposes an improved multi-objective optimization algorithm IMOGWO-SA/D that integrates multiple strategies. This algorithm is based on the MOEA/D framework and transforms the original problem into a series of single-objective sub-problems of coevolution through Chebyshev decomposition, thereby ensuring the diversity of the solution set. For each sub-problem, we adopt the IMOGWO for solution. By introducing adaptive weights and optimizing the file maintenance strategy, our global search and local development capabilities have been enhanced. To overcome the defects that traditional algorithms are prone to fall into local optimum, we creatively embedded the SA mechanism into the position update process of IMOGWO, allowing the algorithm to accept inferior solutions with a certain probability, thereby effectively escaping the local optimum trap and significantly improving the convergence quality and robustness. Ultimately, the

decomposition framework of MOEA/D, the search ability of IMOGWO, and the escape mechanism of SA work in synergy, enabling IMOGWO-SA/D to efficiently and stably obtain a set of Pareto optimal solution sets with good convergence and uniform distribution.

3) To verify the performance of the IMOGWO-SA/D algorithm, we conducted a comparative experiment and selected two representative benchmark algorithms: NSGA-II and MOGWO. Among them, NSGA-II is a classic benchmark algorithm in this field; MOGWO is used to verify the effectiveness of introducing the SA mechanism into IMOGWO. In terms of evaluation metrics, this paper uses the Pareto front and generation distance (GD) to measure the convergence of the solution set and uses the spacing (SP) to evaluate the uniform diversity of its distribution. The experimental results not only confirmed the advantages of the IMOGWO-SA/D algorithm in terms of convergence speed and solution set quality, but also further proved its flexibility and robustness in practical applications through the adaptive analysis of multi-objective scenario allocation.

This paper includes six sections. Section 2 reviews the relevant research. Section 3 established the system model and formal problem definitions, laying a solid foundation for our subsequent work. Section 4 introduces the proposed IMOGWO-SA/D algorithm in detail. Subsequently, Section 5 conducts experimental evaluation and analysis. Finally, Section 6 summarizes this paper and looks forward to future work.

Literature Review

Sensing Technology in Smart Agriculture

The sensing technology of smart agriculture has gone through three development stages: The first stage was mainly based on fixed sensor networks, achieving continuous monitoring at fixed points but with limited coverage; In the second stage, mobile platforms such as drones and agricultural machinery were introduced, expanding the monitoring range but at a relatively high cost; The third stage, namely the MCS stage, utilizes universal intelligent terminals to achieve low-cost and wide coverage. In the field of water resource management, existing research mostly focuses on the Internet of Things monitoring of reservoirs and main canals, with insufficient attention paid to the final-level canal systems. Gong et al. (2025) proposed a method for dynamic water level monitoring and early warning of water diversion channels in water conservancy using multiple sensors at key positions, but the cost of equipment deployment limited its large-scale application. In contrast, MCS does not require dedicated equipment and has greater potential for promotion.

MCS Task Allocation

MCS task allocation can be classified into two types based on the optimization objective: single-objective and multi-objective.

1) Single-objective optimization: Mainly focuses on maximizing platform profits, minimizing costs, or maximizing participation. For example, the literature (Meitei et al., 2022) aimed at maximizing platform profits and designed a task allocation algorithm based on greed. The literature (Shen et al., 2023) aims to minimize the total task cost and proposes a discrete fireworks algorithm introducing predictive information. However, the single-objective optimization method ignores the

contradiction between user cost and platform benefit, which is prone to lead to user churn in practical applications.

2) Multi-objective optimization: Consider the dual demands of both the platform and users simultaneously. For instance, the literature (Yang, 2023) models task allocation as a multi-objective optimization dynamic programming problem, aiming to maximize the bidirectional benefits of workers and platforms (i.e., the balance between platform benefits and worker benefits), and proposes a deep reinforcement learning model based on proximal Policy Optimization (PPO). Literature (Fu et al., 2024) simultaneously optimizes worker utility and platform utility based on reputation index and task proficiency index to achieve Pareto optimality of the benefits of both sides and proposes the Double Population Competitive Evolutionary Algorithm (DCMEA) to efficiently solve multi-objective models. The literature (Li et al., 2025) considered the dual optimization of the overall system benefit and load balancing and proposed a solution algorithm based on the improved Lyapunov optimization theory to achieve the optimal task allocation with load balancing constraints in a dynamic environment.

Multi-objective Optimization Algorithm and GWO

Multi-objective optimization algorithms are effective tools for solving complex optimization problems. The classical algorithms for solving multi-objective optimization problems are mainly divided into two categories: algorithms based on Pareto dominance and algorithms based on decomposition. The former, such as NSGA-II (Deb et al., 2002) and SPEA2 (Zitzler et al., 2001), maintain the diversity of solution sets through non-dominated sorting and congestion calculation. The latter, such as MOEA/D (Zhang et al., 2007), decomposes multi-objective problems into a set of single-objective sub-problems and approximates the Pareto front (PF) through collaborative optimization of the sub-problems.

The Grey Wolf Optimizer (GWO) (Mirjalili et al., 2014) has attracted much attention since its proposal in 2014 due to its advantages such as simple structure, few parameters and easy implementation. This algorithm is a meta-heuristic algorithm inspired by the social hierarchy and hunting behavior of gey wolves in nature and has been successfully applied to various single-objective optimization problems. With the growth of the demand for multi-objective optimization, GWO has also been extended to multi-objective versions. Among them, the most representative one is the Multi-objective GWO (MOGWO) (Mirjalili et al., 2016), which combines the archiving and leader selection mechanism in NSGA-II, enabling the algorithm to effectively handle multi-objective optimization problems. And generate the pareto optimal solution set. However, when dealing with complex multi-objective problems, MOGWO still has issues such as slow convergence speed, being prone to falling into local optimum, and uneven distribution of solution sets. Therefore, this paper combines the decomposition idea with the GWO framework and introduces the Metropolis criterion of simulated annealing (SA) to enhance the algorithm's ability to balance global exploration and local development.

Problem Modeling

The Working Principle of The System

The MCS system for farmland water channel inspection consists of three core entities: the sensing platform (system operation and data management centre), the data requester (demand

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side such as agricultural monitoring institutions, agricultural experts, hydraulic engineers or scientific researchers), and the farmer participant (task execution and data provider). The three collaborate through a closed-loop process of "task requirements - allocation - execution - delivery - rewards". The system life cycle can be divided into five major stages: task publishing (①②), task allocation (③④), task execution (⑤), data delivery (⑥⑦), and reward (⑧). The specific working principle is shown in figure 1.

Figure 1: The Working Principle of The MCS System for Farmland Irrigation Canals

①**Task Request** (initiated by the data requester): The data requester submits the monitoring task requirements for farmland water channels to the sensing platform, clearly stating the monitoring scope (such as a certain village/section of water channel), core indicators (such as siltation thickness, water level height, and facility damage conditions), time requirements (such as completion within 3 days), and quality standards (such as photos containing geographical coordinates and sensor readings being accurate), etc.
②**Task Publishing** (Push from the sensing platform): Based on the task requirements, the sensing platform pushes the task summary (including monitoring key points, time nodes, and regional boundaries) to the farmers within the task coverage area through the APP, text message, or wechat mini program, etc., to attract participants to sign up.
③**Participant selection** (sensing platform screening): The sensing platform automatically matches the most suitable farmer participants based on their location information (whether they are within the task area), ability attributes (such as whether they have a smart phone/sensor device, past task credit score), and availability (whether they have the time to complete the task within the specified period).
④**Task allocation** (assignment by the sensing platform): Based on the matching result of task requirements - farmers' capabilities, the sensing platform sends task allocation notifications to the selected farmers, officially assigning tasks to them, and simultaneously sending task details and operation guidelines.
⑤**Task execution** (farmer participant operation): Farmer participants arrive at the designated water channel monitoring point and use mobile devices (smartphones, tablets, etc.) to collect data (such as siltation, water level, cracks, and debris accumulation) through multimodal sensing methods (photography, sensors, text recording) using mobile devices (smartphones, tablets, etc.).
⑥**Data submission** (farmer uploads raw data): Farmer participants upload the collected raw data to the sensing platform, which automatically verifies data integrity (e.g., whether key fields are missing, whether photos are clear).
⑦**Data delivery** (output results of the sensing platform): The sensing platform validates and integrates the uploaded data, and delivers the data to the data requester.

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⑧**Reward** (payment by the sensing platform): The sensing platform pays the farmer participants according to the quality of the task completion (such as data accuracy, completeness, whether it is submitted on time) and the budget amount, and ensures that the payment is completed within the budget.

This paper focuses on the task allocation strategy. Under the constraints of ensuring high task completion rate and platform budget, taking the maximization of platform benefits and the minimization of farmers' total cost as the optimization objectives, combined with the typical scene characteristics of farmland canal inspection and the heterogeneity of farmers' ability, this paper constructs a multi-objective optimization model, designs an improved multi-objective grey wolf optimization algorithm, and finally realizes the accurate and efficient matching of sensing tasks and farmer participants.

Model Construction

In view of the characteristics of "numerous points and long lines, complex terrain, and concealed problems" in the farmland water channel inspection scenario, as well as the dual optimization requirements of platform benefits and total cost for farmers in the MCS system, this section constructs a multi-objective optimization model that fits the actual scenario. The core of the model is to achieve the collaborative optimization of maximizing platform benefits and minimizing the total cost for farmers through the task allocation strategy, under the premise of meeting the task completion rate, budget constraints and the matching of farmers' capabilities.

System Elements and Decision Variables

Suppose m inspection tasks are released on the sensing platform within a certain period of time, then the task set is represented as $T=\{t_1,t_2,...,t_m\}$, where t_i represents the i-th inspection task, and its attributes include: Monitoring location l_i^t (latitude and longitude coordinates), task type k_i (such as siltation detection, water level monitoring), time window $[wt_i^{start}, wt_i^{end}]$ (earliest start time and latest completion time), quality requirements q_i (such as data accuracy, integrity threshold) and budget upper limit b_i. Meanwhile, if there are n farmers registered on the platform during this period, then the set of farmer participants is represented as $F=\{f_1,f_2,...,f_n\}$, where f_j represents the j-th farmer, and its attributes include: Initial position l_j^f, moving speed v_j, available time window $[wf_j^{start}, wf_j^{end}]$, equipment capability e_j (such as whether sensors are available, camera accuracy), reputation score r_j (based on rate of historical task completion), and the minimum acceptable payment for performing a task c_j^{min}.
The decision variable is defined as the task-farmer allocation matrix $X=[x_{ij}]_{m\times n}$, where:

$$x_{ij} = \begin{cases} 1, & if\ t_i \text{ was assigned to } f_j \\ 0, & \text{else} \end{cases} \tag{1}$$

Objective Function Design

This model contains two mutually restrictive optimization objectives:
1) Maximize platform benefits

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The benefits of the platform need to integrate the rate of task completion and cost control. Let the completion rate of task t_i when carried out by farmer f_j be q_{ij}, which is positively correlated with the farmer's equipment capacity e_j and reputation score r_j, that is, $q_{ij}=\alpha \cdot e_j+\beta \cdot r_j$ (α, β are the weight coefficients). The revenue the platform earns from task t_i is p_i (the fee provided by the data requester), and the remuneration it needs to pay to farmers is c_{ij} (including basic remuneration and distance/time compensation). Therefore, the net income of a single task on the platform is p_i - c_{ij}, and the total benefit is the sum of the net income of all tasks:

$$\max F_1(X) = \sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \times (p_i - c_{ij}) \times q_{ij} \quad (2)$$

Among them, $c_{ij} = c_j^{min} + c_j^d \times d_{ij}$, c_j^{min} is basic remuneration, that is the minimum acceptable payment for performing a task, c_j^d represents cost per unit distance, d_{ij} is the spatial distance between task t_i and farmer f_j (described in detail later).

To conform to the standard form of multi-objective optimization problems, this paper uniformly expresses all objective functions as minimization problems. That is, the objective function $\max F_1(X)$ is transformed by taking the negative sign to become the minimization of the negative platform benefit objective function $\min(-F_1(X))$, which is mathematically equivalent and does not affect the properties of the Pareto front. Therefore, formula (2) can be transformed into formula (3):

$$\min(-F_1(X)) = \min f_1(X) = -\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \times (p_i - c_{ij}) \times q_{ij} \quad (3)$$

2) Minimize the total cost for farmers
The total cost for farmers includes time cost and distance cost. Let the spatial distance between task t_i and farmer f_j be $d_{ij} = dist(l_i^t, l_j^f)$. In this paper, the path distance is adopted to measure d_{ij}. Due to the complex environment of farmland, with obstacles such as field ridges and low-lying areas, the path distance can consider the actual terrain and obstacle factors, accurately reflecting the actual walking distance of participants to reach the task location. It is more in line with the actual needs of the system than the Euclidean distance that only calculates the straight-line distance, which is helpful for farmers to plan routes reasonably and save time and distance costs. In addition, when considering the complexity of the terrain, the terrain factor k can be introduced, namely $d_{ij} = k \times dist(l_i^t, l_j^f)$. Because the cost that farmers spend on carrying out tasks (for example, some tasks only require taking photos or writing records) is smaller than the cost of reaching the target location of the task, it is ignored. Then, the time cost for farmer f_j to perform task t_i is $t_{ij} = d_{ij}/v_j$, the distance cost is $d_{ij} \times c_j^d$. Therefore, the total implementation cost for farmers is:

$$\min f_2(X) = \sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \times (\gamma \times t_{ij} + \delta \times d_{ij} \times c_j^d) \quad (4)$$

Among them, γ and δ are the weight coefficients of time and distance costs, reflecting farmers' sensitivity to time and distance.

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Formalize The Constraint Conditions

To ensure the feasibility of the model and its adaptability to actual scenarios, the following constraints are introduced.

1) Task completion rate constraint: This constraint means that each task can be assigned to at most one farmer and executed by at least one capable farmer. The task completion rate constraint is as follows.

$$\sum_{j=1}^{n} x_{ij} \leq 1, \quad \forall i \in \{1, \dots, m\} \tag{5}$$

$$\sum_{j=1}^{n} x_{ij} \times \mathrm{I}(e_j \geq e_i^{req}) \geq 1, \quad \forall i \in \{1, \dots, m\} \tag{6}$$

Among them, e_i^{req} represents the device capability threshold of task t_i (such as sensor type, camera resolution), and I(·) is the indicator function (with a value of 1 when the conditions are met, and 0 otherwise).

2) Budget constraint: This constraint means that the total payment cost of the platform does not exceed the total budget B, as follows.

$$\sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij} \times c_{ij} \leq B \tag{7}$$

3) Time window constraint: This constraint is used to ensure that the start and completion times of farmers' tasks not only comply with their own available time limits but also meet the time requirements of the tasks. The constraints are divided into two sub-items, corresponding respectively to the "time window available to farmers" and the "time window required for tasks". The two sub-item constraints are as follows.

$$wf_j^{start} \leq tf_j^{start} + t_{ij} \leq wf_j^{end}, \quad \forall i, j 满足 x_{ij} = 1 \tag{8}$$

$$wt_i^{start} \leq tf_j^{start} + t_{ij} \leq wt_i^{end}, \quad \forall i, j 满足 x_{ij} = 1 \tag{9}$$

Among them, tf_j^{start} represents the start time of the task carried out by farmer f_j.

4) Sensing capability matching constraint: This constraint is used to ensure that the equipment capability level of farmers meets the execution requirements of the task, avoiding the failure to complete the task or the failure to meet the quality standards due to capability gaps. This means that only farmers whose sensing abilities meet the requirements of the task are qualified to undertake it. The capability matching constraint is as follows.

$$x_{ij} \times \mathrm{I}\left(e_j \geq e_i^{req}\right) = x_{ij} \quad \forall i, j \tag{10}$$

Problem Definition

Based on the model constructed above, this section formalizes the task allocation problem of farmland water channel inspection as a constrained multi-objective optimization problem (MOP), aiming to find a set of task-farmer matching schemes X that, under the premise of

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meeting all constraints, simultaneously optimize the two objectives of platform benefits and total cost for farmers.
Therefore, the constrained multi-objective optimization problem discussed in this article can be formally defined as:

$$\begin{gathered} min\ [f_1(X),\ f_2(X)] \\ \text{s.t. } constraints\ (5)\sim(10) \\ x_{ij} \in \{0,1\} \quad \forall i,j \end{gathered}$$

The essence of this problem is a multi-objective 0-1 integer programming problem. The objective is to find the Pareto Optimal Set, that is, there is no other solution X' such that:

$$f_1(X') \leq f_1(X) \text{ AND } f_2(X') \leq f_2(X) \tag{11}$$

And at least one goal is strictly better, that is, it is impossible to improve one goal without compromising the other.

Task Allocation Algorithm

Principle of Algorithm

The core principle of IMOGWO-SA/D is decomposition - guidance - perturbation:

1) Decomposition: Use Chebyshev decomposition to break down multi-objective problems into multiple single-objective sub-problems, with each sub-problem corresponding to a weight vector, and conduct parallel optimization to cover different regions of the Pareto front.

2) Guidance: Retain the social hierarchical structure of the GWO (α, β, δ wolves guide ω wolves to update) to ensure the convergence of the algorithm.

3) Perturbation: Introduce the Metropolis criterion of SA to perform local/global perturbation on the updated solution to avoid falling into local optimum.

4) Archiving: Use external files to save Pareto optimal solutions to ensure the diversity and optimality of the solution set.

Algorithm Design

Based on the above core framework, the steps of the IMOGWO-SA/D algorithm are shown in Algorithm 1.

Algorithm 1 IMOGWO-SA/D

Input:

Problem parameters: available tasks set T, available participants set F, task requirements, participant capabilities, cost coefficients and platform benefit coefficients, budget constraint;
Algorithm parameters: population size N (equal to subproblems M), weight vectors $\Lambda=\{\lambda_1,\lambda_2,\ldots,\lambda_M\}$ ($\lambda_k=(\lambda_{k1}, \lambda_{k2})$, satisfying $\lambda_{k1}+\lambda_{k2}=1$, $\lambda_{k1}, \lambda_{k2} \geq 0$), initial temperature T_0, cooling rate α, termination temperature T_{end}, maximum iterations $MaxIter$.

Output:

Pareto optimal solution set A (each solution is a task-participant allocation matrix $X=[x_{ij}]_{m\times n}$, where $x_{ij}=1$ if task t_i is assigned to participant f_j, else 0)

1. Initialize algorithm parameters (N, Λ, T_0, α, T_{end}, $MaxIter$) and problem-specific data (T, F,

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task/participant requirements, cost/benefit coefficients, B).

2. Generate initial population F_{op} with N feasible individuals: For each individual $X \in F_{op}$, ensure:
   $\sum_{j=1}^{n} x_{ij} \leq 1$;
   $x_{ij}=0$ if $e_j < e_i^{req}$;
   $wf_j^{start} \leq tf_j^{start} + t_{ij} \leq wf_j^{end}, \quad \forall i,j满足x_{ij} = 1$;
   $wt_i^{start} \leq tf_j^{start} + t_{ij} \leq wt_i^{end}, \quad \forall i,j满足x_{ij} = 1$;
   $\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \times c_{ij} \leq B$.
3. Decompose the multi-objective problem into $M=N$ subproblems using Chebyshev decomposition: For subproblem k, define the objective function as
   $g_k(X) = max\{\lambda_{k1} \times |f_1(X) - z_1^*|, \lambda_{k2} \times |f_2(X) - z_2^*|\}$
   where:
   $f_1(X) = -\sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \times (p_i - c_{ij}) \times q_{ij}$
   $f_2(X) = \sum_{i=1}^{m}\sum_{j=1}^{n} x_{ij} \times (\gamma \times t_{ij} + \delta \times d_{ij} \times c_j^d)$
   $z^*=(z_1^*, z_2^*)$ is the ideal point (initialized in Step 6)
4. Evaluate each individual in F_{op} using $g_k(X)$ for its corresponding subproblem k.
5. Build external archive A with non-dominated solutions from F_{op} (solutions not dominated by any other in F_{op}; a solution X dominates Y if $f_1(X) \leq f_1(Y)$ and $f_2(X) \leq f_2(Y)$ with at least one strict inequality).
6. Initialize ideal point z^*:
   $z_1^*=\min\{f_1(X) \mid X \in A\}$;
   $z_2^*=\min\{f_2(X) \mid X \in A\}$.
7. Set iteration counter k=0 and current temperature $T=T_0$.
8. While $k \leq MaxIter$ and $T \geq T_{end}$ do
9. For each subproblem k:
   a. Select three best solutions as α_k (optimal), β_k (suboptimal), δ_k (third-optimal) based on $g_k(X)$.
   b. Update positions of ω solutions (remaining individuals in subproblem k) via hierarchical guidance (GWO's social structure):
      i. For each task t_i, get current participant f_j^{curr} (where $x_{ij}^{curr}=1$).
      ii. Get participants f_j^{α}, f_j^{β} f_j^{δ} assigned to t_i in α_k, β_k ,δ_k.
      iii. Calculate selection probability $P(j|i)$ for feasible participants of t_i:
      $P(j|i) = \omega_\alpha \times \mathrm{I}(j = j_\alpha) + \omega_\beta \times \mathrm{I}(j = j_\beta) + \omega_\delta \times \mathrm{I}(j = j_\delta) + \omega_\gamma \times {}^{1}/_{n_i}$
      Where $\omega_\alpha=\omega_\beta=\omega_\delta=2-2k/MaxIter$ (decreasing weights for $\alpha/\beta/\delta$ roles), $\omega_r=1-(\omega_\alpha+\omega_\beta+\omega_\delta)$ (random exploration weight), and n_i is the number of feasible participants for t_i.
      iv. Assign t_i to a new participant f_j^{new} sampled from $P(j \mid i)$, updating X.
10. Apply SA perturbation to each updated individual X':
    a. Generate a neighborhood solution X″ by randomly swapping one task's participant to a feasible alternative (maintaining constraints).
    b. Accept X'' if $\Delta=g_k(X'')-g_k(X')<0$
       else accept with probability $\exp(-\Delta/T)$.
11. Repair infeasible solutions in the population: Adjust assignments to restore compliance with constraints (e.g., if a task is assigned to two participants, reassign one to a feasible alternative).
12. Evaluate the new population using $g_k(X)$ for each subproblem.
13. Update external archive A:
    a. Add non-dominated solutions from the new population to A.
    b. Remove solutions in A that are dominated by new solutions.
    c. If A exceeds size N, prune using crowding distance to maintain diversity.
14. Update ideal point z^*.
15. $T=T\cdot\alpha$.
16. $k=k+1$.
17. End while
18. Return A from the external archive.

Algorithm 1 addresses the unique challenges of farmland canal inspection (e.g., scattered tasks, complex terrain) by:

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1) Strong feasibility: Strict constraint handling in population initialization (Step 2) and repair (Step 11) ensure solutions are practical for real-world MCS.
2) Decomposition for Diversity: Chebyshev decomposition (Step 3) splits the multi-objective problem into subproblems, ensuring the Pareto front covers diverse trade-offs (e.g., platform profit vs. farmer cost).
3) Hierarchical Guidance: GWO's $\alpha/\beta/\delta$ roles (Step 9a) balance exploration (random weights) and exploitation (converging to optimal subproblem solutions).
4) SA for Global Search: The Metropolis criterion (Step 10b) avoids local optima, critical for the "hidden issues" (e.g., canal leaks) that require diverse participant assignments.
5) Archive for Pareto Optimality: The external archive (Step 5,13) preserves non-dominated solutions, enabling decision-makers to choose allocations based on priorities (e.g., max profit vs. min farmer cost).

Experimental Evaluation and Analysis

This section verifies the effectiveness of the IMOGWO-SA/D algorithm in the task allocation of farmland water channel inspection through simulation experiments. It focuses on analyzing the algorithm's convergence, solution set diversity, and scene adaptability, and compares it with classic multi-objective optimization algorithms. Ultimately, it verifies the algorithm's adaptability to farmland scenarios featuring "numerous points, long lines, complex terrain, and hidden problems".

This paper selects two classic multi-objective algorithms as benchmarks. These two classic algorithms are the genetic algorithm NSGA-II based on non-dominated sorting, the traditional multi-objective Grey Wolf Optimizer MOGWO.

Experimental Setup

Dataset

The experimental data is based on the task distribution scenario simulation of the farmland water channel network in Henan Province, China (Figure 2), covering the core feature of "many points and long lines", and includes the following elements.

Figure 2: Simulation Diagram of Inspection Task Distribution

Task set *T*: Generate 100 water channel inspection tasks, distributed in a 50km×50km farmland area, simulating the scattered distribution of water channels. The attributes of each task include: Location coordinates randomly generated, simulating the spatial distribution of the water

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channel; Time window [wt_i^{start}, wt_i^{end}]: Set to [6:00-8:00] or [18:00-20:00] based on the optimal inspection time to avoid high temperatures. Task type k_i: It is classified into three categories according to the inspection task type, 1= Cracks and leaks, 2= siltation and blockage, 3= water level and flow. Sensing requirement e_i^{req}: The threshold of equipment capability required to complete task t_i, such as sensor type, camera resolution; Benefit coefficient p_i: It is linked to the importance of the water channel, p_i=10 for main canals, p_i=5 for branch canals, and p_i=3 for agricultural canals.

Participant set *F*: Generate 50 farmer participants with attributes including: Location coordinates randomly generated, simulating the daily activity range of farmers; Time window [wf_j^{start}, wf_j^{end}]: Set to [6:00-12:00] or [14:00-20:00] according to the farming time to avoid conflicts with farm work; Sensing ability e_j: It is divided into 3 levels based on experience, 1= Novice, 2= proficient, 3= expert; Cost coefficient: Unit distance cost c_j^d=0.5 yuan /km.

Constraint conditions: Platform budget *B*=1,0000 yuan, which is the simulated small-scale water channel inspection budget; Task uniqueness (at most one person can be assigned to each task); Sensing ability matching; Time window matching.

Algorithm Parameter

The key parameters are determined through pre-experiment optimization. The population size *N*=100, which is equal to the number of sub-problems *M*, corresponding to 100 uniform weight vectors $\lambda=(\lambda_1,\ldots, \lambda_i, \ldots, \lambda_{100})$, where λ_i is uniformly sampled from 0 to 1. Initial temperature T_0=100; Cooling rate α=0.95; Termination temperature $T_{end}=10^{-3}$; The maximum number of iterations *MaxIter*=200.

Evaluation Metrics

This paper evaluates the performance of the IMOGW-SA/D algorithm using four metrics, including Pareto front, convergence of solutions, uniform diversity of solutions, and scene adaptability.

1) **Pareto front:** The Pareto front can intuitively display the distribution of non-dominated solutions obtained by each algorithm. Due to the conflicting goals of maximizing platform revenue and minimizing farmer costs, the Pareto optimal solution will form a discrete curve distribution from the top left corner to the bottom right corner. A better algorithm can obtain solutions closer to the ideal point, indicating better overall performance in balancing these two objectives.
2) **Convergence:** Generational Distance (GD) is used to evaluate the accuracy with which the solution set of an algorithm converges towards the True Pareto Front (PF). Since the true Pareto front of the actual problem is unknown, this paper adopts the non-dominated solution set obtained by all algorithms and uses it as the reference set to calculate the GD value. The smaller the GD value is, the closer the solution set is to the true front, and the better the convergence performance of the algorithm. The calculation principle is the root mean square of the Euclidean distance from each individual in the solution set to the nearest individual in the true Pareto front. The calculation formula is as follows:

$$GD = \sqrt{\frac{1}{n}\sum_{i=1}^{n} {d_i}^2} \quad (12)$$

Here, n represents the size of the solution set, and d_i is the Euclidean distance from the i-th solution to the nearest point in the reference set

3) **Diversity:** Spacing (SP) is used to evaluate the uniformity of the distribution of non-dominated solution sets in the target space. The smaller the SP value is, the more uniform the distribution of the solution set is, and the stronger the algorithm's ability to maintain diversity is. The calculation principle is the standard deviation of the Euclidean distance from each individual in the solution set to its nearest neighbor individual. The calculation formula is as follows:

$$SP = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\left(d_i - \bar{d}\right)^2} \quad (13)$$

Here, n is the size of the solution set, d_i is the distance from the i-th solution to its nearest neighbor solution, and $\bar{d}$ is the average of all d_i.

4) **Scene Adaptability:**

- Task Completion Rate (TCR) is used to measure an algorithm's ability to meet core business requirements and is a key indicator for evaluating the effectiveness of the solution set. TCR calculates the percentage of successfully completed tasks to the total number of tasks. To ensure the basic service capacity of the system, it is required that the TCR must reach or exceed 95%. The calculation formula is as follows:

$$TCR = \frac{N_{succ}}{N_{total}} \times 100\% \quad (14)$$

Among them, N_{succ} represents the number of solutions that meet all task requirements, and N_{total} is the total number of tasks.

- The Budget Compliance Rate (BCR) is used to evaluate the economic feasibility performance of the solutions generated by the algorithm, representing the proportion of solutions that strictly comply with budget constraints. As an unbreakable hard constraint, BCR must reach 100% to have practical application value. The calculation formula is as follows:

$$BCR = \frac{N_{feas}}{N_{total}} \times 100\% \quad (15)$$

Among them, N_{feas} represents the number of feasible solutions whose total cost does not exceed the budget limit.

Experimental Results and Analysis

Based on the evaluation metrics in the previous section, after conducting corresponding experiments on the three algorithms, this study took the average of five experiments for each algorithm and compared and analyzed them in terms of convergence, diversity, and scene adaptability.

Pareto Front Analysis

Figure 3 shows that the non-dominated solutions of IMOGWO-SA/D are distributed closer to the lower left region in the target space, with smaller values for f1 (negative platform revenue) and f2 (farmer cost), indicating that the proposed algorithm IMOGWO-SA/D achieves a better

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trade-off between the two conflicting objectives. In contrast, although there is little difference in the Pareto front between MOGWO and NSGA-II, the distribution of their solutions is slightly to the upper right compared to IMOGWO-SA/D, and their overall performance is inferior to IMOGWO-SA/D, indicating that their optimization ability for agricultural canal inspection task allocation is weaker than IMOGWO-SA/D.

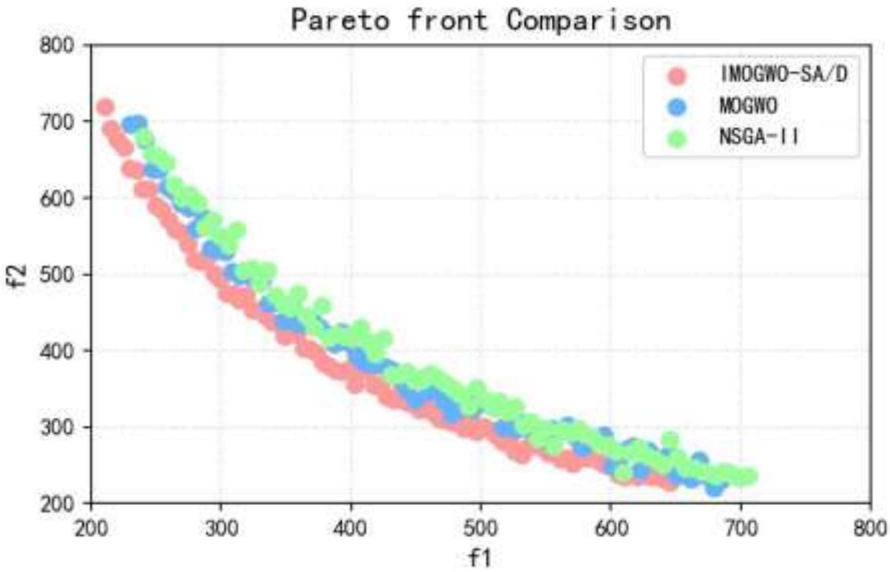

Figure 3: The Pareto Front of Three Algorithms

Convergence Analysis

The box plot in Figure 4 shows the comparison of GD among three algorithms. The proposed algorithm IMOGWO-SA/D achieved the lowest GD median (12.7) and the narrowest distribution range (12.3-13.3), indicating that its solution is closest to the true Pareto front and has the highest convergence stability. In contrast, MOGWO and NSGA-II have higher median GD, 13.3 and 13.7 respectively, and wider fluctuation ranges, with NSGA-II having the weakest performance. These results quantitatively verify that IMOGWO-SA/D has better convergence performance and robustness. In the task allocation problem of agricultural canal inspection, its ability to approximate the optimal Pareto front is superior to MOGWO and NSGA-II.

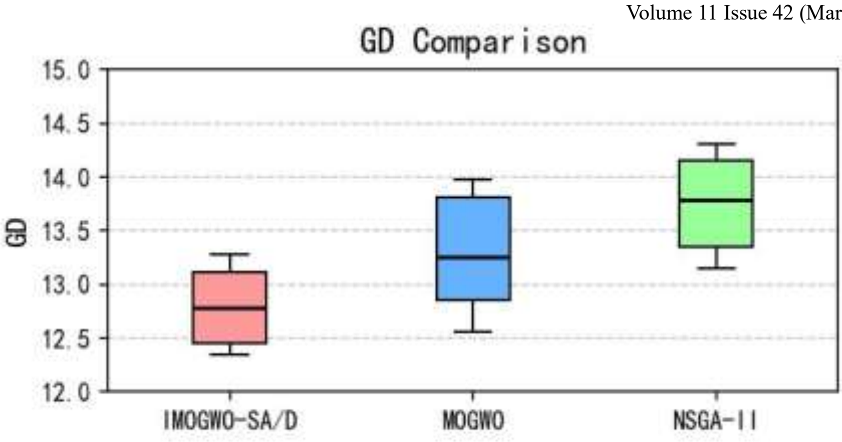

Figure 4: The Convergence of Three Algorithms

Diversity Analysis

The box plot in Figure 5 shows the distribution of SP for the three algorithms. IMOGWO-SA/D achieved a low median SP (3.3) and a compact box, indicating that the distribution uniformity of non-dominated solutions obtained during multiple independent runs is good. The median SP of MOGWO and NSGA-II is slightly higher (3.4), and their overall performance is similar, but neither is as good as IMOGWO-SA/D, showing higher upper edge extremum. These results quantitatively confirm that the proposed algorithm IMOGWO-SA/D not only ensures better Pareto front convergence but also maintains a more uniform and diverse solution set, making it more effective in the task allocation scenario studied in this paper.

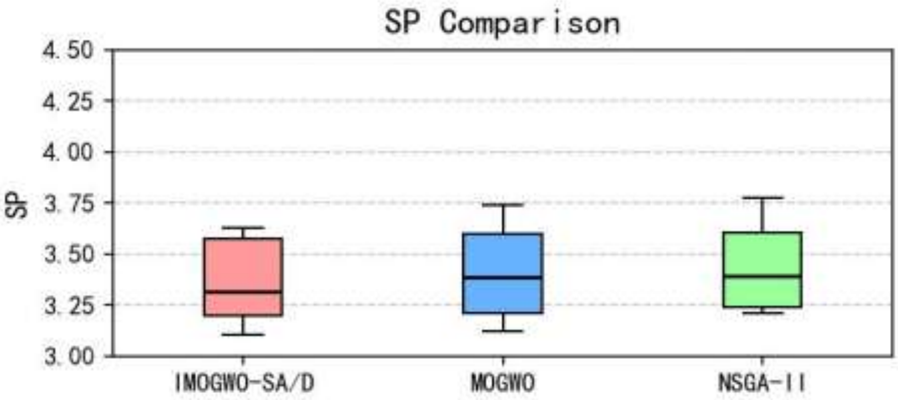

Figure 5: The Diversity of Three Algorithms

Scene Adaptation Verification

Table 1 and Figure 6 respectively present the scene constraint satisfaction of the three algorithms from different perspectives.

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Table 1: The Scene Adaptability of Three Algorithms

Algorithm	TCR	BCR
IMOGWO-SA/D	96.5%	98%
NSGA-II	96%	98%
MOGWO	96.5%	97%

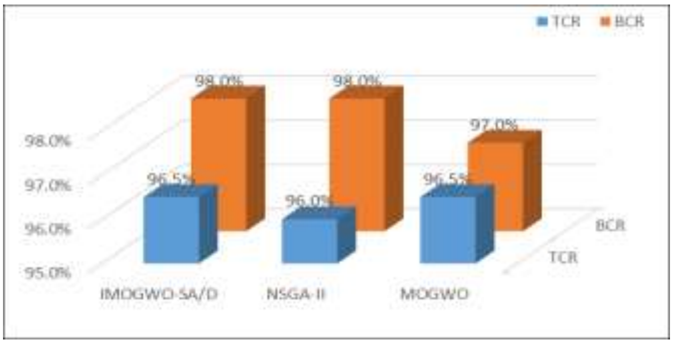

Figure 6: TCR and BCR of Three Algorithms

IMOGW-SA/D achieved higher overall performance with a TCR of 96.5% and BCR of 98%, demonstrating its strong ability to efficiently complete task allocation while maintaining a good economic balance. The BCR of NSGA-II is 98% (the same as IMOGW-SA/D), but the TCR is slightly lower at 96%, indicating a small trade-off between task completion and cost efficiency. The TCR of MOGWO is comparable to that of IMOGWO-SA/D, at 96.5%, but its BCR has decreased to 97%, reflecting weaker performance in optimizing the trade-off between benefits and costs. Overall, IMOGWO-SA/D strikes the best balance between high task completion and optimal benefit-cost ratio, confirming its superior adaptability and robustness to the practical task allocation scenario studied in this paper.

Analysis of Algorithm Efficiency

Overall Evaluation

In order to evaluate the computational burden of each algorithm, this section analyzes the performance of the algorithm from the perspective of time complexity. Although IMOGW-SA/D introduces the SA mechanism, its overall computational cost is not higher than algorithms based on non-dominated sorting. The computational costs of the three algorithms are shown in Table 2.

Table 2: Time Complexity of Three Algorithms

Algorithm	Core computing overhead	Theoretical time complexity (per generation)
NSGA-II	Non-dominated Sorting	$O(MN^2)$或 $O(MN\log N)$
MOGWO	Position Update	$O(N{\cdot}D)$
IMOGWO-SA/D	Position Update and SA	$O(N{\cdot}D{\cdot}L)$

In Table 2, *N* represents the Population Size; *M* represents the number of Objectives (2 here); *D* represents the Dimensions of the decision variable. G represents the maximum number of iterations; *L* represents the number of iterative steps for local search.

Comparative Analysis

The computational bottleneck of NSGA-II lies in the Fast Non-dominated Sorting of each generation. Its time complexity is $O(MN^2)$. When the population size is large, the calculation of congestion distance and the comparison of dominance relations will consume a large amount of CPU time, resulting in a slower convergence speed in high-dimensional problems.

However, the time complexity of IMOGWO-SA/D mainly consists of two parts: the global search $O(N{\cdot}D)$ of the grey Wolf framework and the local neighborhood search $O(N{\cdot}L)$ of SA. Although the SA mechanism introduces additional local iteration overhead (making the single iteration time slightly longer than that of MOGWO), it accelerates the convergence process of the algorithm. More importantly, compared with NSGA-II, IMOGWO-SA/D avoids non-dominated sorting at the $O(N^2)$ level and instead adopts an environment selection strategy based on reference points. Therefore, in actual operation, IMOGWO-SA/D achieves the best trade-off between computational efficiency and solution quality while maintaining a high-precision solution set.

Conclusion

This paper addresses the pain points of high operation and maintenance costs and low inspection efficiency of farmland irrigation channels in the context of smart agriculture and proposes an improved mobile crowd sensing task allocation algorithm (IMOGWO-SA/D) based on the multi-objective grey wolf optimization algorithm. By deeply analyzing the scene characteristics of farmland water channels, such as "many points, long lines, and complex terrain", an optimization model that simultaneously maximizes platform benefits and minimizes farmers' execution costs was constructed, solving the problem of insufficient adaptability of conventional optimization algorithms in agricultural scenarios. At the algorithm design level, an innovative combination of the Chebyshev decomposition strategy and the simulated annealing mechanism was adopted. This not only reduces the computational complexity through the decomposition idea but also enhances the global search ability through the Metropolis criterion of simulated annealing, achieving a balance between algorithm convergence and solution set distribution. The simulation experiment results show that IMOGWO-SA/D outperforms classic algorithms such as NSGA-II and MOGWO in multiple key indicators. In summary, the proposed method not only improves the quality of multi-objective optimization solutions theoretically but also provides a practical and feasible technical path for building a low-cost and wide-spread distributed monitoring system for agricultural infrastructure. Future research will further consider the diverse preferences of participants and the prediction of their daily activity trajectories to explore the possibility of resource optimization under the opportunity sensing model.

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