Study on Crop Planting Planning Based on Goal Programming and Particle Swarm Optimization

Yangsong He [#], Yao Ge [#, *], Zibo Deng [#]

College of Mathematical Science, Shenzhen University, Shenzhen, China, 518000

* Corresponding Author Email: dcdengzibo@163.com

[#]These authors contributed equally.

Abstract. Faced with the challenges posed by global population growth and climate change, enhancing agricultural production efficiency and resource utilization, as well as scientifically planning crop planting schemes to adapt to various field characteristics and market demands, has become a core issue in modern agriculture. In actual production, numerous constraints complicate the planning of crop planting schemes. To address this issue, this study establishes a goal programming model for production planning, predicting the annual profit and planting scheme over the next seven years in two scenarios and solving it with the Particle Swarm Optimization (PSO) method. On this basis, a dynamic adjustment of the inertia weight method was introduced to accelerate convergence. Results show that, with this model, the average annual profits for the two scenarios reached 5,385,399 and 6,145,969 yuan, representing increases of 7.70% and 22.91% compared to 2023. The convergence speed with dynamic inertia weight adjustment was 2.92 and 2.09 times faster than without .This study provides a practical tool for enhancing agricultural efficiency, boosting economic returns, and supporting smart agriculture while addressing global food security and sustainability challenges.

Keywords: PSO, Goal Programming, Crop Planting Planning, Dynamic Pricing Rules.

1. Introduction

With the continuous growth of the global population and the challenges climate change poses to agricultural production, improving agricultural production efficiency and resource utilization has become an urgent issue. In this context, how to scientifically and rationally plan crop planting schemes to maximize land use efficiency and crop revenue while adapting to the characteristics of different land plots and market demand fluctuations has become a core issue in modern agricultural production.

Traditional crop planting decisions often rely on experience and historical data, lacking systematic quantitative analysis and optimization methods. In recent years, with the continuous development of data analysis technology and intelligent algorithms, more and more researchers have applied advanced optimization algorithms to crop planning. These technologies provide scientific support for farmers facing complex planting decisions through quantitative analysis to improve crop planting efficiency, achieving higher yields and benefits. This study uses the PSO algorithm. Particle Swarm Optimization (PSO) algorithm has the characteristics of simplicity and strong adaptability, and has been widely applied in multiple fields such as resource optimization allocation, engineering optimization, financial investment, and bioinformatics [1-2].

In this study, based on realistic planting constraints, a goal programming model is established with the objective function of maximizing revenue. Given the large scale and high dimensionality of this problem, the PSO algorithm was used to solve it. However, by analyzing the convergence curve of the solution, it was found that the convergence speed was slow when using the basic PSO algorithm. To address this, a dynamic inertia weight adjustment was introduced to improve convergence speed [3].

2. Data Preprocessing

The data for this study is sourced from https://www.mcm.edu.cn/, firstly, preliminary observation and analysis were conducted on four datasets, and no visually significant missing or abnormal values were identified. Then, SPSS was used for a more systematic data screening and testing process to further confirm that there were no statistically significant anomalies in the datasets. To gain a deeper understanding of data features, this article explores the visualization of two key variables: planting area and plot area. The analysis results show that the pie charts of planting area and plot area exhibit a high degree of similarity, suggesting that there may be a close correlation or a certain degree of homogeneity between the two, providing important clues for subsequent data analysis and model construction.

As shown in Figure 1, cereal crops (including grains and legumes), as basic agricultural products, usually dominate in terms of planting area; Vegetable crops (including vegetables and vegetable legumes) occupy a certain proportion in the pie chart due to their wide variety and planting on different land types; Edible mushrooms have relatively small planting areas due to their high planting conditions and technical requirements.

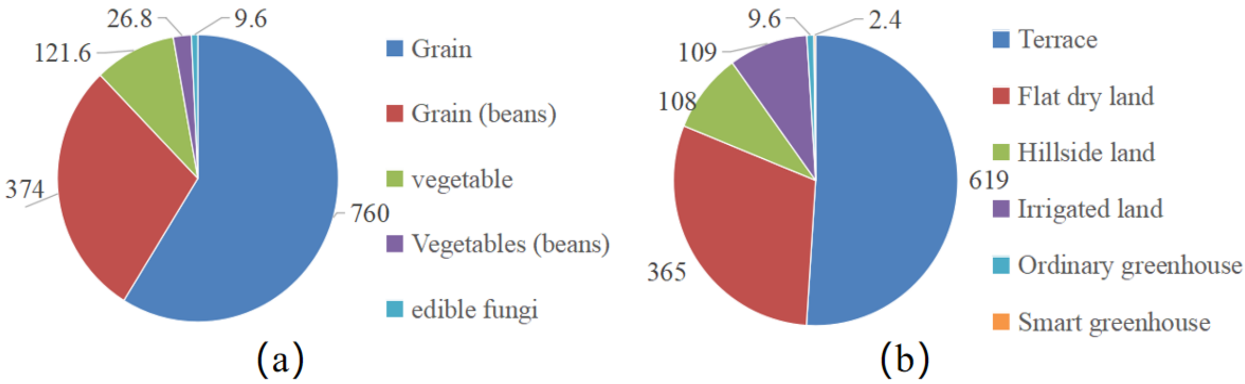

Figure 1. Planting Area Distribution Pie Chart a and Plot Area Distribution Pie Chart b.

Assuming that the expected sales volume, planting cost, yield per acre, and sales price of various crops will remain stable relative to 2023, which is shown in the Table 1.Then based on the current season's sales of crops planted each season, calculate the yield of each crop in 2023, and obtain a profit of 5 million yuan for 2023 without using the target planning method, which will be used as the expected sales volume condition in the development of the 2024-2030 plan.

Table 1. Expected Sales Volume Results for 2023 (Partial).

season	Types	Expected sales	season	Types	Expected sales
only season	soybean	57000	Season 1	cowpea	0
only season	black soya bean	21850	Season 2	cowpea	36240
only season	Red beans	22400	Season 1	sword bean	2880
only season	Mung bean	33040	Season 2	sword bean	0
only season	Climbing beans	9875	Season 1	kidney bean	6480
only season	Wheat	170840	Season 2	kidney bean	0

3. Crop Optimization with Goal Programming and PSO

3.1. Goal Programming

To address the challenge of formulating optimal crop planting strategies for rural areas, an optimization approach capable of handling multiple variables, numerous constraints, and diverse economic scenarios is required. Given the complexity of the problem, which encompasses different land types, a variety of crop species, planting costs, sales prices, and dynamic changes in market demand, we have chosen to construct a goal programming model [4].

By solving this mathematical programming model, we aim to obtain the optimal crop planting strategies under various market conditions, including situations where crop yields are unsold or sold at reduced prices.

3.1.1. Dynamic Pricing Rules

$$p_{ijt}^{k} = p_{ijt\,min}^{k} + \left(p_{ijt\,max}^{k-1} - p_{ijt\,min}^{k-1}\right) \times \frac{Q_{ijt}^{k} - x_{ijt}^{k} \cdot y_{ijt}^{k}}{Q_{ijt}^{k}} \tag{1}$$

Here, p_{ijt}^{k} represents the selling price of crop *j* planted on plot *i* during season *t* in the *k*-th year for that specific season.

$p_{ijt\,max}^{k}$And $p_{ijt\,min}^{k}$ denote the maximum and minimum possible selling prices, respectively, for crop *j* on plot *i* during season *t* in the *k*-th year. These prices are determined based on historical data.

Q_{ijtk} Indicates the expected sales volume of crop *j* planted on plot *i* during season *t* in the *k*-th year, which is assumed to be equal to the actual yield of each crop in 2023.

The variables x_{ijt}^{k} and y_{ijt}^{k} represent the cultivated area of crop *j* on plot *i* and the yield per unit area of crop *j* on plot *i* during season *t* in the *k*-th year, respectively. Their product gives the total production volume.

The core of this formula lies in adjusting the selling price based on deviations between actual and expected production volumes. When the actual production volume $x_{ijt}^{k} \cdot y_{ijt}^{k}$falls below the expected sales volume Q_{ijt}^{k}, the selling price increases (due to reduced supply and relatively increased demand), and vice versa, the price decreases. This adjustment helps farmers compensate for losses by raising prices when production is insufficient and stimulate sales by lowering prices when there is excess production [5].

3.1.2. Decision Variables

The decision variable, denoted as x_{ijt}^{k} , represents the area of plot *i* devoted to crop *j* in season *t* during year *k*. This serves as the fundamental unit in the optimization process and is directly linked to subsequent revenue calculations and resource allocations. The setting of this variable permits granular control over the planting scale of each plot, each season, and each crop, providing flexibility and precision for subsequent optimization analyses.

3.1.3. Objective Function

To make the model more realistic, two different types of unsold situations are designed for analysis.

Situation One: Maximizing the total economic revenue for the current year (the *k*-th year):

$$Maximize\ Z_k = \sum_{i=1}^{M}\sum_{J=1}^{N}\sum_{t=1}^{T}\left(p_{i,j,t}^{k} \cdot y_{i,j,t}^{k} \cdot x_{i,j,t}^{k} - c_j^{k} \cdot x_{i,j,t}^{k}\right) \tag{2}$$

M is the total number of plots;

N is the total number of crop types;

T is the number of seasons (*T*=2, meaning there are two seasons per year).

Situation Two: The portion exceeding the expected sales volume is sold at a 50% discount to the sales price in 2023.

The production volume of the excess portion is expressed as $s_{i,j,t,k}$

$$s_{i,j,t,k} = max\left(0,\ x_{i,j,t,k} \cdot y_{i,j,t,k} - D_{i,j,t,k}\right) \tag{3}$$

$$Maximize\ Z_k = \sum_{i=1}^{M}\sum_{J=1}^{N}\sum_{t=1}^{T}\left(p_{j,k} \cdot min\left(x_{i,j,t,k} \cdot y_{i,j,t,k},\ D_{i,j,t,k}\right) + 0.5 \cdot p_{j,k} \cdot s_{i,j,t,k} - c_{i,j,t,k}\right) \tag{4}$$

$p_{i,j,t}^{k}$: The selling price of crop *j* in the *k*-th year, measured in yuan per half kilogram.

$x_{i,j,t,k} \cdot y_{i,j,t,k}$: The production volume of crop *j* planted on plot *i* during season *t*, measured in half kilogram. Here, $y_{i,j,t,k}$represents the yield per acre of crop *j*, measured in half kilogram per acre.

$D_{i,j,t,k}$: The upper limit of expected sales volume for crop *j* on plot *i* during season *t*, measured in half kilogram.

$s_{i,j,t,k}$: The portion that exceeds the upper limit of sales volume, measured in half kilogram, which is sold at a 50% discount.

$c_{i,j,t,k}$: The planting cost of crop *j* in the *k*-th year, measured in yuan per acre.

3.1.4. Constraints

1) The total cultivated area for each crop remains unchanged: The total cultivated area for each crop remains constant during the exchange process, satisfying the following condition:

$$\sum_{i=1}^{M}\sum_{t=1}^{T} x_{i,j,t}^{k} = A_j, \ \ \forall j = 1,2,\dots,N \tag{5}$$

Aj represents the total cultivated area for crop *j*.

2) Land area constraint: The total cultivated area for each plot cannot exceed its land area, and this holds for each season and plot:

$$\textstyle\sum_{j=1}^{N} x_{i,j,t}^{k} \le A_j, \ \ \forall j = 1,2 \tag{6}$$

3) Crop-land type matching constraint:

4) Based on crop suitability and land type, the following constraints are set:

$$x_{i,j,1}^{k} = 0, \ \ x_{i,j,2}^{k} = 0, \ \ \forall j \ \in [16,1,7,\dots,41] \tag{7}$$

Flat dry land, terraced fields, and hillside land: Only grain crops (excluding rice) can be planted.

$$\begin{cases} \sum_{t=1}^{\mathrm{T}} x_{i,j,t}^{k} \le 2A_j, \ \ \forall j \in [27,28,29,30,31,32,33,34] \\ x_{i,j,2}^{k} = 0, \ \ \forall j \ne \ 16 \\ x_{i,j,1}^{k} = 0, \ \ \forall j = 35,36,37 \\ x_{i,j,2}^{k} = 0, \ \ \forall j \ne 35,36,37 \end{cases} \tag{8}$$

Ordinary greenhouse: The first season can be used to grow various vegetables, while the second season can only be used to grow edible mushrooms.

$$\begin{cases} x_{i,j,1}^{k} \ne 0, \ \ \forall j \ne \ 35,36,37 \\ x_{i,j,2}^{k} \ne 0, \ \ \forall j = \ 35,36,37 \end{cases} \tag{9}$$

Smart greenhouse: Both seasons of the year can be used to grow vegetables, but it is not allowed to grow Chinese cabbage, white radish, or red radish.

$$x_{i,j,t}^{k} = 0, \ \ \forall j \in [35,36,37] \tag{10}$$

5) Crop Rotation Restrictions:

For land plots that can only be planted in a single season (such as flat dry land, terraced fields, and hillside land), the same crop cannot be planted for two consecutive years.

$$x_{i,j,t}^{k} + x_{i,j,t}^{k+1} \le A_i, \ \ \forall i \ \in [1,2,\dots,26], \forall i, \ \ t = 1 \tag{11}$$

For land plots that can be planted in multiple seasons (such as irrigated land and greenhouses), the same crop cannot be planted within consecutive two seasons.

$$x_{i,j,t}^{k} + x_{i,j,t+1}^{k} \le A_i, \ \ \forall i,j,t \tag{12}$$

6) Legume Crop Rotation Restriction:

Each land plot must be planted with a legume crop at least once within six seasons.

$$\sum_{j\in S_{beans}}\sum_{t=1}^{6} x_{i,j,t}^{k} \geq \frac{A_i}{6}, \quad \forall i = 1,2,\cdots,M \tag{13}$$

The set of legume crops is denoted as S_{beans}.

7) Non-negative Constraint:

The decision variable $x_{i,j,t}^{k}$ must be non-negative; otherwise, the obtained result will be meaningless.

$$x_{i,j,t}^{k} \geq 0, \quad \forall i,j,t,k \tag{14}$$

8) Estimated Sales Volume Restriction:

$$x_{i,j,t}^{k} \cdot y_{i,j,t}^{k} \leq Q_{i,j,t}^{k} \tag{15}$$

Due to oversupply and unsold products in the first scenario, causing waste, we add a production limit. Specifically, the production volume of each product in a certain quarter should not exceed the estimated sales volume determined by the production volume of each product in 2023.

3.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is an optimization algorithm based on swarm intelligence, whose core idea is to gradually approach the optimal solution through the cooperation of a group of particles in the search space [6-10]. The specific steps are as follows:

Firstly, randomly generate a group of particles in the search space and initialize their positions and velocities, which includes the following three parts:

- Define particle swarm: Each particle represents a possible crop planting plan, and its position is a vector. Each element of the vector represents the planting area of different crops on different plots of land.
- Initialize particle swarm: Randomly generate initial positions for num_ particles. We set a total of 40 particles and set the initial velocity v of each particle to a small random value.
- Set parameters: individual learning factor $c_1 = 1.5$, social learning factor $c_2 = 1.5$, and maximum iteration times $max\_iter = 2000$.

Then define the fitness function and calculate the fitness value of each particle based on the objective function (i.e. maximizing total profit). The fitness value is used to evaluate the quality of the solution represented by the particle.

For each particle, update its velocity according to the following formula:

$$v_{ij}^{t+1} = w \cdot v_{ij}^{t} + c_1 \cdot r_1 \cdot \left(p_{best\,j} - x_{ij}^{t}\right) + c_2 \cdot r_2 \cdot \left(g_{best\,j} - x_{ij}^{t}\right) \tag{16}$$

Among them, *v* is the velocity of the *i* particle in the *j* dimension, x_{ij}^{t} is its position, p_best_j is the best position in the history of the particle, that is, the individual optimal solution, g_best_j is the best position of all particles in the *j* dimension, that is, the global optimal solution, and r_1, r_2 is a random number between [0, 1]. Adjust the position of particles based on the updated speed:

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \tag{17}$$

This formula represents that the new position of a particle i in the d dimension is its current position plus the updated velocity. Ensure that the planting area is nonnegative: If there are any negative values in the updated position, set it to 0.Meet the total area limit of the plot: Ensure that the total planting area of crops on all plots does not exceed the total area of the plot.

After the above steps, update individual optimality p_best_j and update global optimality g_best_j.

Finally, repeat the evaluation and update steps for the above process until the maximum number of iterations *max_iter* is reached. During this process, the particle swarm can gradually approach the optimal solution, thereby obtaining the optimal solution.

4. Results

4.1. The establishment of the PSO model

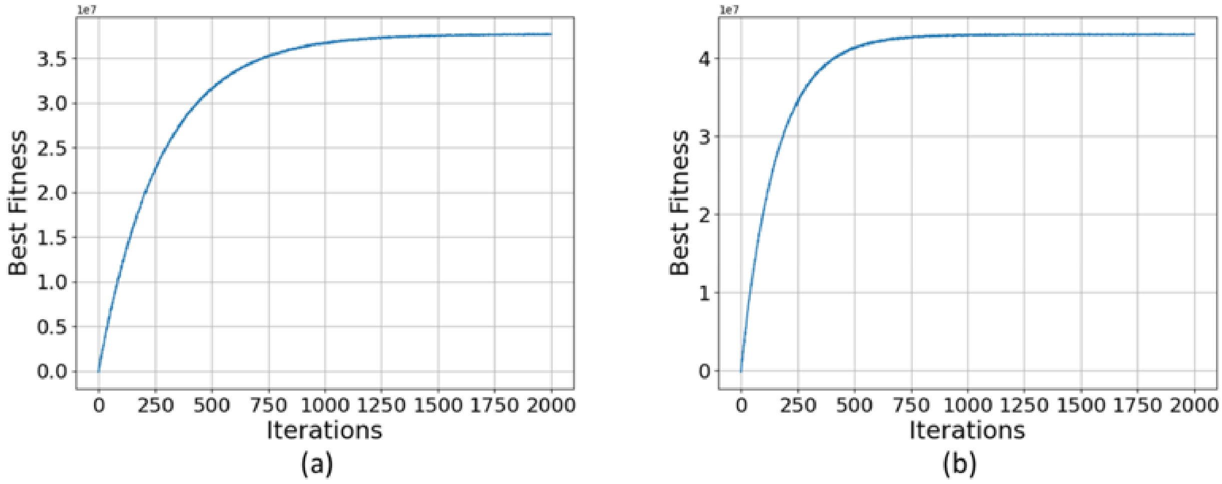

Figure 2. Iteration results of the particle swarm algorithm for Scenario 1 and Scenario 2.

Due to the large scale of the problem, this study focuses on the number of iterations in goal programming and the final total profit to evaluate the effectiveness of the algorithm. The convergence results of the original PSO method used to solve the problem are shown in Figure 2. To further verify the accuracy of the model, the sales price was adjusted to the upper and lower bounds constrained by the dataset, and the corresponding upper and lower limits of total revenue were obtained, as shown in Figure 3. Finally, the convergence curve after introducing dynamic inertia weight adjustment is shown in Figure 4.

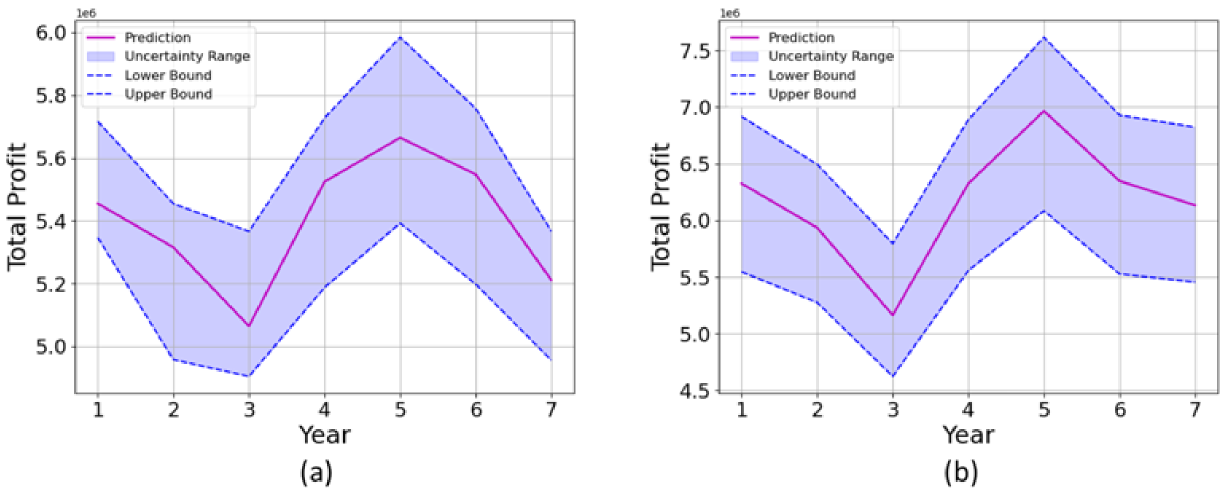

Figure 3. Predicted total revenue results per year for Scenario 1 and Scenario 2.

4.2. Analysis of experimental results

From Figure 2, it can be observed that Scenario 1 converges after approximately 1500 iterations, reaching a profit of 37,697,796 yuan, while Scenario 2 converges after about 800 iterations, reaching 43,021,785 yuan. With the addition of dynamic inertia weight adjustment, the number of iterations for Scenario 1 was reduced to 372, and Scenario 2 to 527, significantly accelerating convergence by 2.92 times and 2.09 times, respectively. Figure 3 shows that, despite yearly constraints causing fluctuations in profit, both scenarios maintained high revenue levels. Even under the lower bound, where all crop prices were set to the minimum, only two years in Scenario 1 and one year in Scenario 2 had lower profits compared to 2023. Over seven years, the average profit increased by 7.70% in Scenario 1 and 22.91% in Scenario 2. Under the constraints of the set termination conditions, the proposed method proved feasible and improved agricultural production profits.

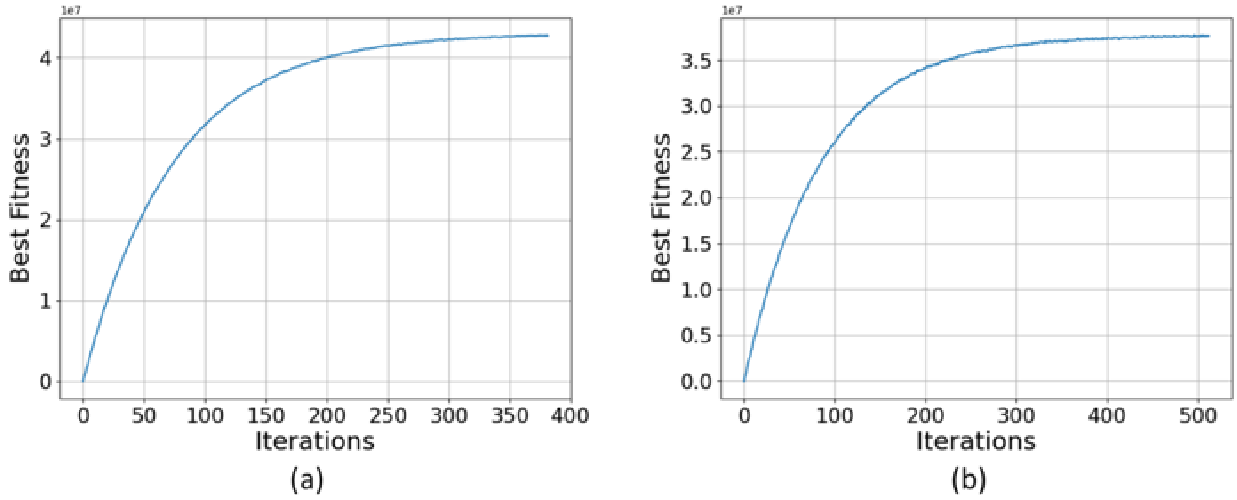

Figure 4. Optimized iteration results of the model for Scenario 1 and Scenario 2.

5. Conclusions

This study investigates a crop planting planning method based on goal programming and particle swarm optimization (PSO) to address challenges posed by global population growth and climate change in agriculture. By establishing a goal programming model and introducing dynamic inertia weight adjustments into the PSO algorithm, the study optimizes crop planting strategies under multiple constraints, significantly enhancing agricultural production efficiency and economic returns. The experimental results demonstrate that the optimized model markedly accelerates convergence and achieves substantial average annual profit growth in two scenarios (7.70% and 22.91%, respectively).

The approach provides a practical tool for crop planning, particularly in resource optimization and the advancement of smart agriculture. Future research could explore integrating more complex market dynamics and other intelligent algorithms into the model to enhance flexibility and adaptability. Such advancements could further promote its application in addressing global food security and sustainability challenges.

References

[1] Li Muhan, Zhao Xiping, Li Yiping Multi objective optimization allocation of water resources in Yangquan City using particle swarm optimization algorithm [J] Computer Simulation, 2024, 41 (9): 460-464

[2] Zhang Libiao, Zhou Chunguang, Ma Ming, et al. solving multi-objective optimization problems based on particle swarm algorithm [J]. Journal of Computer Research and Development, 2004, (07): 1286-1291.

[3] Zhang Qian, Zhang Jianfeng, Li Tao, et al. Improvement of particle swarm optimization algorithm and its application in agricultural water resources allocation [J]. Journal of Drainage and Irrigation Machinery Engineering, 2020, 38(06): 637-642.

[4] Zhang Yuxun, Ren Li, Zhang Bei, et al. Task allocation and practice for medical institutions based on linear programming [J]. Smart Health, 2022, 8(28): 22-26.

[5] Gao Jianan, Tai Minglang, Cui Siyu, et al. Research on dynamic pricing and replenishment decisions for vegetable commodities [J]. Mathematical Modeling and Its Applications, 2024, 13(02): 47-56.

[6] Wang Xun, Half kilogram Yanzun. Research on supplier order allocation method based on multi-objective programming [J]. China Management Informationization, 2024, 27(02): 123-126.

[7] Li Muhan, Zhao Xiping, Li Yiping. Multi-objective optimization allocation of water resources in Yangquan City based on particle swarm optimization [J]. Computer Simulation, 2024, 41(09): 460-464.

[8] Wang Rongjie, Zhang Liang. Multi-UAV task allocation based on game theory and hybrid particle swarm [J]. Computer Science, 2024, 1-10.

[9] Ma Youxin. Optimization of long-distance urban-rural water pipeline using improved multi-objective particle swarm optimization algorithm [J]. Groundwater, 2024, 46(05): 153-155.

[10] Hu Half kilogrambiao, Li Jiachen, Zhang Zhijie, etc Urban drone path planning based on multi-objective particle swarm algorithm [J] Aeronautical Computing Technology, 2024, 54 (5): 38-42