Agricultural Planting Optimization Based on Parallel Stochastic Programming and Improved Slime Mould Algorithm

Yongqi Chen[1,a,*], Sijie Ma[1,b]

[1]Department of E-commerce, South China University of Technology, Guangzhou, Guangdong, China

[a]2952325017@qq.com, [b]202230090497@mail.scut.edu.cn

*Corresponding author

Keywords: Crop Planting Optimization, Parallel Stochastic Programming, Slime Mould Algorithm, Good Lattice Points, Opposition-Based Learning, Agricultural Planning

Abstract: Agricultural planting optimization under limited land resources and market uncertainties represents a critical challenge in rural revitalization. This paper proposes a novel optimization approach combining parallel stochastic programming with an improved Slime Mould Algorithm (SMA). The methodology introduces a two-subsystem parallel structure to reduce computational complexity, and incorporates the newsvendor model concept to handle price uncertainties. The SMA is enhanced through Good Lattice Points initialization and lens imaging opposition-based learning strategies. Experimental results demonstrate that the improved algorithm achieves superior convergence and solution quality compared to traditional methods. The optimization model generates significant economic benefits, with the discounted sales scenario showing a 58% profit increase. The parallel optimization framework effectively balances computational efficiency and solution quality, while the improved SMA shows enhanced exploration and exploitation capabilities. This research provides practical guidance for agricultural planning and demonstrates the effectiveness of the proposed method in handling complex crop planting optimization problems.

1. Introduction

The implementation of rural revitalization strategy constitutes a crucial component in building socialism with Chinese characteristics in the new era. In China's modernization process, agricultural production efficiency enhancement and rural economic development face numerous challenges[1]. Among these challenges, optimizing crop planting structures under limited arable land resources remains a critical issue for improving agricultural production efficiency.

Recent years have witnessed extensive research on crop planting optimization. Regarding optimization methodologies, Yang et al.[2]proposed a fuzzy multi-objective linear fractional programming approach to address crop planting structure optimization. Adamo et al.[3]employed constraint programming techniques to investigate crop planting layout optimization in sustainable agriculture, while Li et al.[4]examined agricultural land use structure optimization from the perspective of sustainable resource utilization. Given the uncertainties inherent in agricultural production, stochastic programming methods have gained widespread application. Notably, Ren et al.[5]developed a multi-objective stochastic fuzzy programming method for optimizing agricultural water and land resource allocation, and Fu et al.[6]constructed an interval two-stage stochastic robust programming model to resolve agricultural multi-water source allocation issues. However, existing studies exhibit several limitations: (1) most research is confined to single crops or simple crop combinations, lacking comprehensive optimization for complex multi-crop systems; (2) insufficient consideration of market uncertainties makes it difficult to address price fluctuation risks; (3) relatively limited research on multi-period planting decision problems.

To address these challenges, this study proposes a crop planting optimization method based on stochastic programming and an improved slime mould algorithm. The main innovations include: (1) construction of a stochastic programming model with multi-dimensional constraints, capable of simultaneously optimizing multiple crop planting schemes; (2)development of a parallel

  DOI: 10.25236/icmmct.2025.018

programming strategy based on logical partitioning, effectively reducing computational complexity; and (3) design of two algorithm improvement strategies - good lattice point initialization and lens imaging opposition-based learning, significantly enhancing solution efficiency.

2. Methodology

This section develops a two-stage parallel stochastic programming model for agricultural planting optimization, based on an analysis of the problem's demands and constraints.

2.1. Parallel Optimization via Logical Decomposition

In crop planting decisions, various factors need to be considered, such as land use, crop selection, and regional distribution. If a global optimization model were constructed directly, the large number of decision variables would lead to significant computational complexity. To address this, we employ a logical decomposition approach to divide the problem into two subsystems: the first subsystem handles the planting planning of food crops (excluding rice), while the second subsystem deals with other crops (e.g., vegetables, edible fungi). By independently modeling and solving these two subsystems in parallel, we can reduce the overall complexity and improve computational efficiency.

2.2. Stochastic Programming Framework Inspired by the Newsvendor Model

The core of this problem lies in optimizing crop planting to maximize profits. Given that crop prices are uncertain, the idea of the newsvendor model is adapted to this problem. The newsvendor model balances the costs of stockouts and overstocking to determine the optimal order quantity, thus maximizing expected profit. In the context of this problem, although the sales volume is known, crop prices are uncertain and may lead to unsold inventory or discounted sales. Therefore, by incorporating price uncertainty, we model the crop planting process using stochastic programming to optimize the planting areas of various crops.

2.3. Mathematical Model for the First Subsystem

2.3.1. Objective Function Design

The objective of the first subsystem is to maximize overall profit, taking into account revenue from normal sales, discounted sales, and planting costs. The primary decision variables in this model are the planting areas of each crop and their corresponding sales volumes. The objective function is expressed as follows:

$$max\theta(x,V_i) = |\sum_{t=1}^{7}\sum_{i=1}^{15}\left\{V_i\cdot\left[min\left(\sum_{j=1}^{26}P_{ij}\cdot x_{ijt},Q_i\right)+S\cdot\left(\sum_{j=1}^{26}P_{ij}\cdot x_{ijt}-Q_i\right)\right]-C_i\cdot\sum_{j=1}^{26}x_{ijt}\right\}-\lambda\cdot\sum_{t=1}^{7}\sum_{i=1}^{15}\sum_{j=1}^{26}\mathrm{sgn}(x_{ijt}) \quad (1)$$

Where V_i is the selling price of crop i, Q_i is the predicted sales volume, C_i represents the planting cost, P_{ij} is the yield of crop i on plot j, x_{ijt} is the planting area of crop i on plot j during year t, S is the discount factor, and λ is the penalty coefficient.

2.3.2. Deterministic Approximation of Stochastic Programming

Due to the randomness of prices, traditional stochastic programming methods can be complex. To simplify the problem, we use the Sample Average Approximation (SAA) method to transform the stochastic problem into a deterministic one. By drawing N samples $\xi_1,\xi_2,\dots,\xi_N$ from the uniform distribution of prices and approximating the expected value using the average of these samples, the objective function becomes:

$$max\frac{1}{N}\sum_{a=1}^{N}\theta(x,V_i) = \sum_{t=1}^{7}\sum_{i=1}^{15}\left\{V_i\cdot\left[min\left(\sum_{j=1}^{26}P_{ij}\cdot x_{ijt},Q_i\right)+S\cdot\left(\sum_{j=1}^{26}P_{ij}\cdot x_{ijt}-Q_i\right)\right]-C_i\cdot\sum_{j=1}^{26}x_{ijt}\right\}-\lambda\cdot\sum_{t=1}^{7}\sum_{i=1}^{15}\sum_{j=1}^{26}\mathrm{sgn}(x_{ijt}) \quad (2)$$

This transformation simplifies the problem, converting a stochastic optimization problem into a deterministic one that is easier to solve.

2.3.3. Constraints Formulation

The constraints include land area limitations, crop planting area restrictions, continuity constraints on crop planting, and crop rotation requirements for legumes. The specific constraints are as follows:

Land Area Constraint: The planting area on each plot must not exceed its available area:

$$\sum_{i=1}^{15} x_{ijt} \leq A_j \tag{3}$$

Crop Planting Area Constraint: The planting area of each crop must meet a minimum area requirement:

$$x_{ijt} \geq lb_1 \tag{4}$$

Continuous Crop Planting Constraint: Prevent the same crop from being planted continuously on the same plot:

$$x_{ijt-1} \cdot x_{ijt} = 0 \tag{5}$$

Legume Crop Rotation Constraint: Ensure that each plot grows a legume crop at least once every three years:

$$\sum_{i \in \{1,2,3,4,5\}} \left(x_{ijt-1} + x_{ijt} + x_{ijt+1}\right) > 0 \tag{6}$$

These constraints ensure that the crop planting plan meets agricultural production requirements while preventing land resource waste and ecological damage.

2.3.4. Mathematical Model for the Second Subsystem

The second subsystem's objective is similar to the first subsystem, aiming to maximize profits. The decision variables, objective function, and constraints in the second subsystem follow the same structure as those in the first subsystem, with only adjustments in crop identifiers, plot areas, and other relevant parameters.

The specific objective function is:

$$\max \frac{1}{N} \sum_{a=1}^{N} \theta(x', V_i') = \sum_{t=1}^{7} \sum_{i=1}^{80} \left\{ V_i' \cdot \left[\min\left(\sum_{j=1}^{28} P_{ij}' \cdot x_{ijt}', Q_i' \right) + S \cdot \left(\sum_{j=1}^{28} P_{ij}' \cdot x_{ijt}' - Q_i' \right) \right] - C_i' \cdot \sum_{j=1}^{28} x_{ijt}' \right\} - \lambda \cdot \sum_{t=1}^{7} \sum_{i=1}^{80} \sum_{j=1}^{28} \operatorname{sgn}\left(x_{ijt}'\right) \tag{7}$$

The constraints, including land area, planting area, and crop rotation, are identical to those of the first subsystem.

2.4. Implementation of Improved Slime Mould Algorithm

Based on the objective function discussed above, this model is classified as a nonlinear programming problem, necessitating the use of heuristic optimization algorithms. The Slime Mould Algorithm (SMA) is an optimization algorithm that simulates the foraging behavior of slime mould in nature. It leverages the slime mould's food source tropism, oscillatory contraction behavior, and network adaptability in multi-food source environments to approximate optimal solutions through iterative position updates. The core mechanisms can be summarized into three rules: approaching food, surrounding food, and acquiring food.

2.4.1. Basic SMA Steps

The standard SMA implementation follows these key steps:

Step 1) Initialization: Randomly generate positions for a group of slime mould individuals in the solution space, with population size N, where the i-th slime mould's position is denoted as x_i, i = 1, 2, ..., N.

Step 2) Fitness Evaluation: Evaluate the fitness $S(x_i)$of each individual x_i using the objective function of the planning model.

Step 3) Update weights and parameters according to:

$$W=\begin{cases}1+r\times\log\left(\frac{bF-S(i)}{bF-wF}+1\right), & S(x_i)>S(x_i)\\ 1-r\times\log\left(\frac{bF-S(i)}{bF-wF}+1\right), & S(x_i)\le S(x_i)\end{cases} \tag{8}$$

$$b=1-\frac{t}{T} \tag{9}$$

$$\mathrm{a}=\mathrm{arctanh(b)} \tag{10}$$

Where $r\in[0,1]$ is a random number, t denotes iteration count, bF and wF represent the best and worst fitness values in the current iteration.

Step 4) Update individual positions following:

$$\mathrm{X(t+1)}=\begin{cases}\mathrm{r\times(ub-lb)+lb}, & \mathrm{r<z}\\ \mathrm{X_b(t)+v_b(W\times X_A(t)-X_B(t))}, & \mathrm{z\le r<p}\\ \mathrm{v_c\times X(t)}, & \mathrm{p\le r}\end{cases} \tag{11}$$

Where ub and lb are upper and lower bounds, $X_b(t)$ and $X(t)$ represent the best position and current position at iteration $t, X_A(t)$ and $X_B(t)$ are randomly selected individuals, $v_b\in[-a,a]$ and $v_c\in[-b,b]$ are random numbers.

2.4.2. Good Lattice Points Initialization Strategy

To address the unstructured nature of the objective function, which precludes gradient-based optimization, we employ Good Lattice Points (GLP) initialization. The GLP set for a population of size n is constructed as:

$$P_n(i)=\{(r_1i_1,r_2i_2,\dots,r_ni_n)\}, i=1,2,\dots,n \tag{12}$$

Where:

$$r_i=\mathrm{mod}\left(2\cos\left(\frac{2\pi i}{k}\right)n_i,1\right) \tag{13}$$

The mapping to the feasible domain is given by:

$$X_j^i=a_j+P_n(i)\left(b_j-a_j\right) \tag{14}$$

Where a_j and b_j represent dimensional bounds.

2.4.3. Lens Imaging Opposition-Based Learning Strategy

To combat premature convergence in complex optimization problems, we introduce a lens imaging opposition-based learning strategy. Considering a global optimal position P projected from an individual X_b of height h, the opposite solution P^* is derived through:

$$\frac{\frac{a_i+b_i}{2}-P}{P^*-\frac{a_i+b_i}{2}}=\frac{h}{h^*} \tag{15}$$

Setting $\frac{h}{h^*}=n$ yields:

$$P^*=\frac{a_i+b_i}{2}+\frac{a_i+b_i}{2n}-\frac{P}{n} \tag{16}$$

The parameter n is dynamically adjusted according to:

$$n=(1+(t/T)^{1/2})^{10} \tag{17}$$

Where smaller n values generate wider-ranging opposite solutions while larger values produce more localized solutions, enabling both exploration and exploitation.

3. Results and Discussion

3.1. Crop Planting Optimization Results

The optimization results for the year 2024 demonstrate significant differences between inventory stagnation and discounted sales scenarios. Under the inventory stagnation scenario, the total profit reaches 5,867,830.75 yuan, showing only a marginal 2% decrease compared to the 2023 profit of 5,980,748.25 yuan. In contrast, the discounted sales scenario yields a substantially higher total profit of 9,465,955.75 yuan representing a remarkable 58% increase. This significant improvement can be primarily attributed to the expanded cultivation area of high-margin crops such as cucumber.

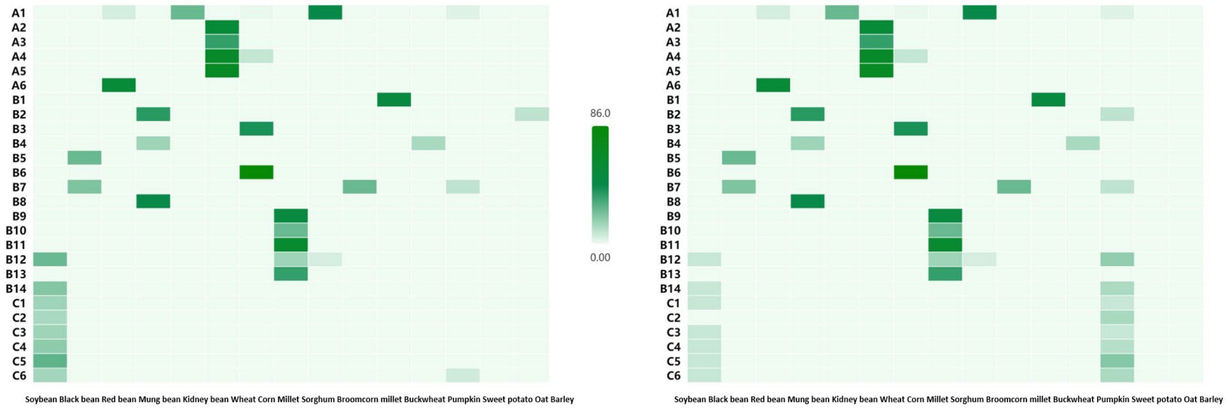

Figure 1 First subsystem: Inventory stagnation (left) and discounted sales (right)

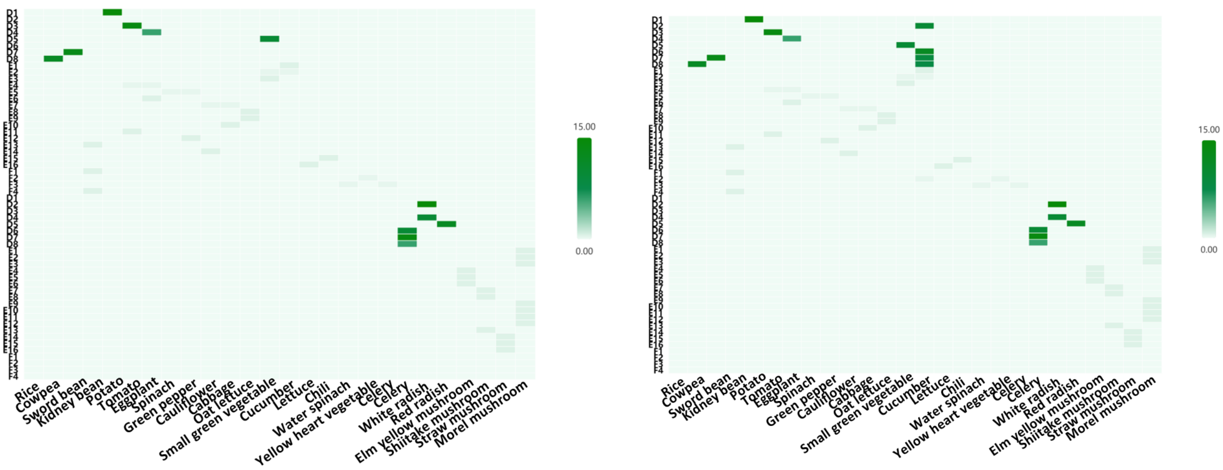

Figure 2 Second subsystem: Inventory stagnation (left) and discounted sales (right)

The heat maps presented in Fig. 1 and Fig. 2 reveal distinctive patterns in crop allocation across both subsystems. The sparse nature of these matrices indicates a concentrated planting strategy, with the discounted sales scenario exhibiting slightly more dispersed patterns compared to the inventory stagnation case. This dispersion occurs because excess production can still be sold at a discount, leading to a redistribution of cultivation areas from low-margin to high-margin crops when the profit threshold condition $\text{Profit}_{\text{high}} = \text{Profit}_{\text{low}}/S$ is satisfied.

3.2. Margin Analysis and Strategic Insights

A detailed examination of the profit margins, as shown in Table 1, reveals crucial insights into optimal crop allocation strategies.

Table 1 Profit Margins by Crop Type

	Rice	Chinese Cabbage	White Radish	Red Radish	Poplar Mushroom	Shiitake	White Mushroom	Morel
Margin (yuan/mu)	2820	10500	9500	9250	284500	74000	150000	90000

The optimization model eliminates rice cultivation due to its low profit margin, enabling expansion of high-margin vegetables like Chinese cabbage, white and red radish in irrigated fields. This reallocation significantly improves overall profit in the discounted sales scenario, validating our model's effectiveness in optimizing crop allocation while balancing profits with practical constraints across different agricultural zones and seasons.

4. Conclusion

This study presents a novel approach to crop planting optimization by combining stochastic programming with an improved Slime Mould Algorithm. The proposed parallel stochastic programming framework effectively addresses computational challenges through logical decomposition into two subsystems, while the integration of newsvendor model concepts provides robust handling of market uncertainties. These findings not only validate the effectiveness of our approach in agricultural planning but also provide valuable insights for implementing rural revitalization strategies and improving agricultural production efficiency. Future research could explore the incorporation of environmental factors, more sophisticated price uncertainty models, and climate change impacts, while expanding the application to diverse agricultural planning scenarios and geographical regions.

References

[1] HAN B, JIN X, GU Z, et al. Research progress and key issues of territory consolidation under the target of rural revitalization[J]. Journal of Natural Resources, 2021, 36(12): 3007-3030.

[2] Yang G, Li X, Huo L, et al. A solving approach for fuzzy multi-objective linear fractional programming and application to an agricultural planting structure optimization problem[J]. Chaos, Solitons & Fractals, 2020, 141: 110352.

[3] Adamo T, Colizzi L, Dimauro G, et al. Crop planting layout optimization in sustainable agriculture: A constraint programming approach[J]. Computers and Electronics in Agriculture, 2024, 224: 109162.

[4] Hongqing L I, Wenqi L I, Fei Z. Optimal land use structure for sustainable agricultural development—A case study in Changsha County, south central China[J]. Journal of Resources and Ecology, 2021, 12(2): 203-213.

[5] Ren C, Li Z, Zhang H. Integrated multi-objective stochastic fuzzy programming and AHP method for agricultural water and land optimization allocation under multiple uncertainties[J]. Journal of cleaner production, 2019, 210: 12-24.

[6] Li Y P, Liu J, Huang G H. A hybrid fuzzy-stochastic programming method for water trading within an agricultural system[J]. Agricultural Systems, 2014, 123: 71-78