Research on Agricultural Economic Crop Planting Decision-making Based on Greedy-Simulated Annealing Algorithm

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Abstract. With the global population explosion and accelerated urbanization, food security and sustainable agricultural development are facing serious challenges, especially in China. How to make full use of limited arable land resources to meet the increasingly diversified demand for farm products has become a key issue in agricultural modernization. Under the actual situation of a mountain village in North China, this paper constructs a mixed integer linear programming model to optimize the planting scheme and improve local planting efficiency. The model combines a greedy algorithm with a simulated annealing algorithm, takes crop varieties and economic benefits into account, ensures a reasonable balance between grain crops and economic crops, and determines the planting priority of different crops based on key indicators such as planting cost, mu yield, and market price. The results show that the economic crop planting option is more advantageous under the stagnant sales scenario, with a profit scale of 2.32 million yuan; In contrast, the grain crop planting option is more economically efficient under the sales scenario with falling prices, with an economic crop profit scale of 13.57 million yuan. The study provides theoretical support and optimization references for rural planting planning with limited arable land resources and helps promote agricultural modernization and sustainable rural development.

Keywords: Agricultural Economic Optimization, Mixed-Integer Linear Programming, Greedy Algorithm, Simulated Annealing, Crop Cultivation Strategy.

1. Introduction

As the global population continues to grow and urbanization accelerates, food security and sustainable agricultural development have become pressing issues for governments to address [1]. China's red-line policy for arable land guarantees national food security by protecting basic farmland. However, as market demand and consumer preferences evolve, farmers are facing increasingly complex challenges in crop selection and planting decisions [2]. Therefore, under the constraints of limited arable land resources, how to scientifically plan crop planting structures to improve land use efficiency and meet diversified market demands has become a core issue in the modernization of China's agriculture [3].

To address the problem of optimizing crop planting structures in the context of limited arable land, this paper introduces both the greedy algorithm and the simulated annealing algorithm to efficiently solve the complex planting decision-making problem. The greedy algorithm is primarily used to find an approximate solution to the optimal one, achieving fast computation by selecting the local optimum at each step [4]. Greedy algorithms have been widely applied in agricultural cropping planning; for instance, Sharma et al [5]. employed crop rotation optimization with greedy algorithms to improve agricultural productivity. Furthermore, Wang, F. et al. [6] applied the algorithm to optimize rice planting patterns, enhancing irrigation resource efficiency. However, the greedy algorithm tends to fall into local optima, thus failing to guarantee global optimality. To overcome this limitation, the paper introduces the simulated annealing algorithm, inspired by the physical annealing process, which adopts a random perturbation strategy to search for the optimal solution globally, effectively avoiding the local optimum dilemma [7]. In agricultural cropping planning, simulated annealing has proven effective in addressing complex resource allocation problems [8]. For example, Benvenga et al. applied it to optimize crop cultivation and significantly improved farmland utilization efficiency, while Liu, X. et al [9]. successfully reduced agricultural input costs by optimizing fertilization schemes using simulated annealing.

Additionally, the hybrid algorithmic strategy in this study incorporates advanced theories of multivariate optimization, such as the multi-objective optimization framework proposed by Rangarajan et al. [10], which enhances the accuracy of resource utilization. In terms of model design, a multi-objective function is employed to evaluate the integrated optimization of factors such as production, cost, and market price [11]. Rahimi, M. et al. [12] further demonstrated that hybrid optimization algorithms hold significant application value in solving multidimensional decision-making problems in agriculture.

In this study, a mountain village in North China is selected, and a mixed-integer linear programming model is developed by systematically collecting and classifying crop data into grain crops and economic crops, incorporating key indicators such as planting cost, yield per mu, and market price. The planting order of grain crops and economic crops is determined to optimize the allocation of limited arable land resources. By combining the greedy algorithm and simulated annealing algorithm, the proposed planting scheme is validated by simulating market scenarios, such as stagnant sales and reduced-price sales, to evaluate the performance of the algorithm under different assumptions [13].

2. Data Sources and Visualization Analysis

The data of this study comes from https://www.mcm.edu.cn, considering the more complex data structure, to better analyze and understand the data, it is necessary to analyze the data in advance before the model is constructed to solve the problem, in order to initially understand the general situation of the data, so as to facilitate the analysis of the subsequent research.

2.1. Seasonality of crops

Exploring the seasonality of crops can help farmers plan their planting time more rationally and generate more outputs within the limited time and arable land constraints. Seasonality exists for economic crops (double cropping) and not for grain crops (single cropping). The seasonality of crops is shown in Figure 1. Further exploration shows that grain crops are all single-season crops and double-season crops are all economic crops, so only economic crops need to be analyzed for seasonality later.

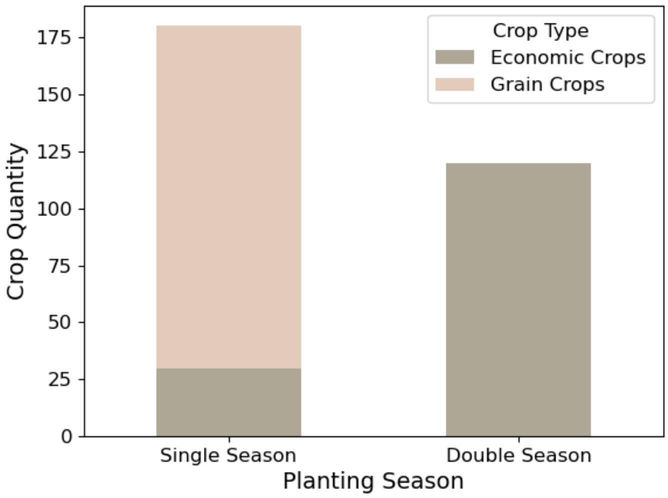

Figure 1. Seasonal distribution of crops

2.2. Allocation of watered land

The watered land is a complex use plot, capable of growing economic crops (double season) and grain crops (single season rice), as shown in Figure 2. However, the grain crop rice can only be grown on watered land. To simplify the problem, this paper allocates fixed plots to rice cultivation to meet the market demand, to eliminate the cross terms in the plot allocation problem.

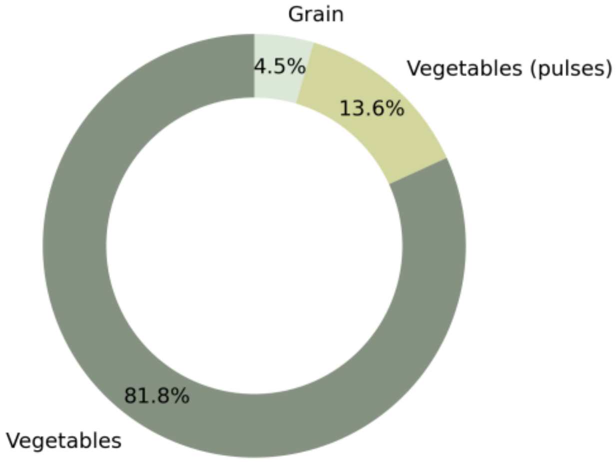

Figure 2. Distribution of crop species on watered land

2.3. Variety richness of various types of plantable crops

The variety of crops that can be planted can help farmers diversify planting risks, ensure the stability of the overall yield, and enhance the adaptability to market demand[14]. The variety richness of each type of crop is shown in Figure 3. Analysis shows that the number of crops in each category is more evenly distributed, of which economic crops (vegetables, vegetables (beans), and edible fungi) account for nearly 70% of the number of varieties, and the space for choosing varieties is larger. There are relatively few grain crops to choose from, which is closely related to the orientation of diversified consumer demand.

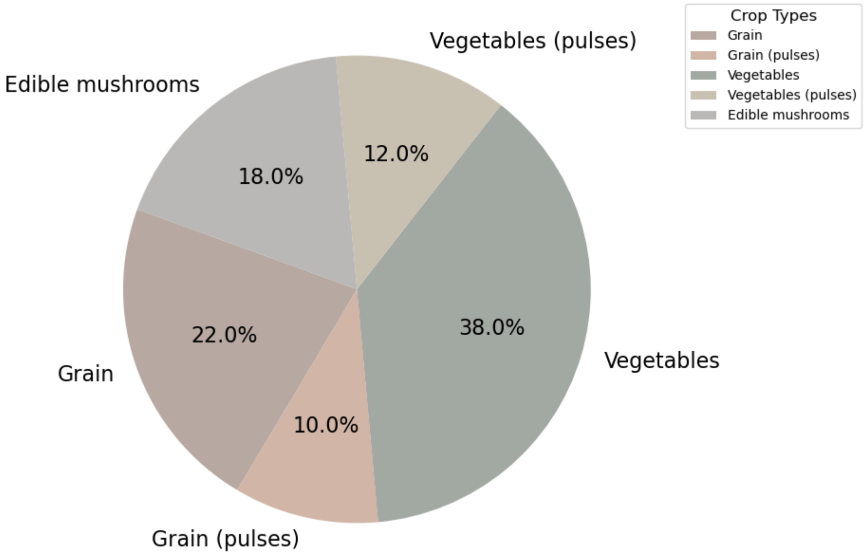

Figure 3. Proportion of species distribution

3. Application of Mixed Integer Linear Programming in Crop Cultivation

3.1. 3.1 Greedy algorithm solution

The planting and harvesting of economic crops are affected by seasonal factors, making the timing of planting particularly challenging [15]. In this context, the greedy algorithm, an optimization method based on local optimal selection, can effectively address this problem. By selecting the current optimal decision at each step, the greedy algorithm expects the final solution to be close to the global optimal. It also helps to rationally allocate limited resources in the preliminary stage, considering the impact of seasonality on economic crops [16].

First, define the crop set $E = \{e_1, e_2, \dots, e_n\}$ and the plot set $F = \{f_1, f_2, \dots, f_m\}$, where each crop e_i is characterized by several parameters: R_i represents the expected profit per unit area (i.e., revenue minus cost), D_i denotes the planting demand or the total required area for crop e_i, and P_i indicates the planting priority score. The priority score P_i is calculated using a weighted formula that integrates expected profit, sales volume, and market demand:

$$P_i = \alpha \times R_i + \beta \times S_i + \gamma \times M_i \tag{1}$$

Where S_i is the expected sales volume, M_i is a market demand indicator, and α, β, γ are weight coefficients reflecting the relative importance of each factor. After calculating P_i for all crops, sort them in descending order to create a prioritized list $E' = \{e_{(1)}, e_{(2)}, \dots, e_{(n)}\}$, ensuring that $P_{(1)} \geq P_{(2)} \geq \dots \geq P_{(n)}$.

The greedy algorithm then iteratively allocates planting areas for each crop in the prioritized list. For each crop $e_{(i)}$, allocating it to suitable plots while considering the yield rate Y_j of each plot f_j. The objective is to maximize the profit by prioritizing plots that provide the highest yield. The area allocated to crop $e_{(i)}$ on plot f_j is determined as:

$$A_{ij} = min(A_j, \frac{D_{(i)} - \sum_{k=1}^{j-1} A_{jk}}{Y_j}) \tag{2}$$

Where A_j is the total available area of plot f_j. The total profit for each crop $e_{(i)}$ is subsequently calculated using the formula:

$$Profit_{(i)} = \sum_{j=1}^{m} (A_{ij} \times Y_j \times R_i) \tag{3}$$

This ensures that the allocation process prioritizes plots with higher yields to maximize revenue. The available area of each plot is updated after each allocation, with the remaining available area calculated as:

$$A'_j = A_j - A_{ij} \tag{4}$$

And the remaining demand for crop $e_{(i)}$ is updated as:

$$D'_{(i)} = D_{(i)} - \sum_{j=1}^{m} (A_{ij} \times Y_j) \tag{5}$$

If the demand for any crop is not fully satisfied, or if there are remaining unallocated areas, re-evaluating the allocation strategy. The conditions for re-evaluation are:

$$\sum_{i=1}^{n} D'_{(i)} > 0 \quad or \quad \sum_{j=1}^{m} A'_j > 0 \tag{6}$$

If either condition holds, further adjustments are made to the allocation to optimize the overall planting efficiency. The algorithm produces a preliminary planting plan by allocating areas for each crop based on their priority scores, subject to the constraints of plot availability and crop demand. The overall profit achieved by this initial allocation is given by:

$$Total\ Profit = \sum_{i=1}^{n} Profit_{(i)} \tag{7}$$

Since the greedy algorithm focuses only on the current optimal choice, it may not lead to the globally optimal solution [17]. Therefore, further tuning and optimization are required through a more sophisticated optimization method, such as mixed integer linear programming.

3.2. Mixed integer linear programming model

To further optimize the planting scheme based on the initial solution, a mixed integer linear programming (MILP) model is introduced. This model can handle multiple uncertainties and consider complex constraints [18]. The objective is to maximize the total profit of economic crops while satisfying constraints such as planted area, crop rotation requirements, and market demand.

The objective function aims to maximize the total profit from economic crops, calculated as sales proceeds minus planting costs and overproduction losses. The model considers multiple constraints. Firstly, each economic crop cannot be grown on the same plot more than once. Second, the same crop is not planted consecutively on the same plot to ensure a crop rotation system is in place; each plot is planted with a legume crop at least once every three years to promote sustainable soil utilization. In addition, the total production of each crop must meet the expected sales volume. The total acreage is restricted so that it cannot exceed the available arable land area, while the acreage planted with each crop must be non-negative. To determine whether a particular crop is planted on a given plot, the model uses binary variables.

To address overproduction, the model calculates the fraction of excess production for each crop and handles it accordingly: for stagnant overproduction, it is deducted directly from the objective function, while overproduction sold at a reduced price is valued at 50 percent of the original price.

$$overproduction = max\ (0, \sum_i x_{i,e} \cdot P_{i,e} - E_e) \tag{8}$$

$$Revenue\ from\ price\ reduction\ sales = overproduction \cdot \frac{S_e}{2} \tag{9}$$

In summary, the following model is developed:

$$maxZ_e = \sum_i \sum_e \left[(S_e \cdot P_{i,e} \cdot x_{i,e} - C_e \cdot x_{i,e)} - overproduction \right] \tag{10}$$

$$s.t. \begin{cases} x_{i,e} \le A_i \cdot z_{i,e} \\ \sum_i \sum_d x_{i,d} \ge \frac{1}{3} \times Total\ Available\ Land \\ \sum_i y_{i,e} \ge E_e \\ \sum_i \sum_e x_{i,e} \le Total\ Available\ Land \\ x_{i,e} \ge 0 \\ z_{i,e} \in \{0,1\} \end{cases} \tag{11}$$

With the above constraints and objective functions, the mixed-integer linear programming model can optimize the crop planting scheme while ensuring the rational allocation of resources and the satisfaction of various types of agricultural production requirements. Based on the preliminary solution provided by the greedy algorithm, the MILP model improves the economic efficiency and feasibility of the planting scheme through global optimization[19], which further enhances the model's practicality and optimization capability.

4. Optimization Process of Simulated Annealing

4.1. Solution steps

Firstly, an initial solution is generated in the initialization phase of the algorithm by randomly assigning crop types and planting areas to each plot, forming a preliminary planting scheme. The initial temperature and cooling rate are also set at this stage.

Next, the advantages and disadvantages of the current solution are evaluated using the fitness function. The fitness function targets total profit, taking into account factors such as yield and overproduction treatments. Additionally, it includes a planting diversity bonus and a crop rotation penalty to encourage plots that meet the requirements of legume rotation and ensure the sustainable use of soil.

To explore new cropping options, the algorithm generates a neighbor solution by adjusting the crop type or acreage of a randomly selected plot. These small changes increase the diversity of the solution space and help the algorithm escape from local optima [20].

Regarding the acceptance criterion, the algorithm not only accepts a neighboring solution that is superior to the current solution but also accepts a suboptimal solution with a probability of $P = \exp\left(\frac{\Delta f}{T}\right)$, where Δf denotes the fitness difference between the current solution and the neighbor solution, and T represents the current temperature. This acceptance probability decreases as the temperature decreases, allowing the algorithm to explore extensively at high temperatures and focus on local optimization at lower temperatures [21].

In each iteration, the current solution is updated according to the acceptance criterion while the temperature is gradually reduced, allowing the exploration process to converge. The algorithm eventually terminates when the temperature drops to a predefined low value (e.g.10-3） or when the maximum number of iterations is reached, returning the current optimal solution.

4.2. Solution results

Examples of some of the results of the simulated annealing algorithm solution are shown in the Table 1 below:

Table 1. Simulated annealing solution for optimal planting scenario (base case: lagging)

Plot Name	Cabbage	Olea Europe	Cucumber	Lettue	Yellow Cabbage	Celery
D1	-	-	0.318	-	-	-
D2	0.731	0.346	0.522	0.257	0.487	0.346
D3	0.234	0.645	0.512	0.337	0.398	0.314
D4	-	-	0.517	-	-	-
D5	0.283	0.323	0.672	0.397	0.154	0.299

The total profit results of the two treatment programs for the two types of crops separately are shown in the Table 2 below:

Table 2. Results of total profit for the stagnant and discounted sales treatment scenarios

	Profit in case of Lagging sales (¥million)	Profit in case of discount (¥million)
Grain Crops	11.55	13.57
Economics Crops	2.32	2.16

The results of the study showed that the total profit of grain crops in the case of stagnant sales was 11.55 million yuan, while the total profit increased to 13.57 million yuan when sold at a reduced price (at a 50 percent discounted price), significantly boosting returns. In contrast, the total profit of economic crops was 2.32 million yuan in the case of stagnant sales, while it decreased to 2.16 million yuan when sold at a reduced price. This suggests that grain crops benefit from a price reduction strategy, while economic crops are better suited to retaining inventory to avoid a decline in profits.

5. Conclusion

This paper provides a research idea and framework combining the greedy algorithm and simulated annealing algorithm for application in the field of agricultural economics, especially in the solution of crop planting planning and optimization problems. The greedy algorithm overcomes the limitation of local optimum through the rapid generation of preliminary solutions, while the simulated annealing algorithm overcomes the limitation of local optimum through global optimization, and the combination of the two can achieve better planting decisions under complex constraints and improve the efficiency of agricultural production. By comparing with traditional methods, this paper demonstrates that the framework can effectively deal with common multivariate problems in agricultural economics, providing a flexible and efficient tool for agricultural economic decision-making. Therefore, the methodology and framework adopted in this study have a wide range of application potentials and can provide strong support for optimal resource allocation, production decision-making, and market regulation in the agricultural field.

In conclusion, this study provides a novel theoretical perspective and solution for crop planting optimization. Future research holds significant potential not only in refining algorithms and expanding models but also in exploring the integration of diverse data sources, multi-dimensional optimization of economic and environmental objectives, and responsive strategies to dynamic market demands. Moreover, the proposed methodologies and approaches can be extended to other fields of resource allocation and optimization, thereby advancing agricultural modernization and sustainable development.

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