Research on Optimal Crop Planting Problem Based on Fuzzy Planning Modeling

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Abstract. With the increasing importance of rural economic development, the optimization of crop planting strategies on limited arable land has become crucial. This study utilizes fuzzy planning models and particle swarm optimization (PSO) algorithms to improve production efficiency and reduce cultivation risks. The fuzzy model tackles the uncertainties in crop prices and sales through affinity functions, while the PSO algorithm searches iteratively for optimal solutions under constraints such as soil degradation and crop rotation. The case study results reveal clear trends: under Scenario 1 (2024–2030), crops 1 and 2 maintained high planting areas due to stable market demand, while crops 3 and 4 showed significant fluctuations. In Scenario 2, there was a sharp increase in the acreage of crop 5 after 2028, reflecting the model's adaptive response to market dynamics. These findings demonstrate the model's capability to optimize resource allocation under uncertainty, providing scalable solutions for rural agricultural planning. By combining fuzzy logic with swarm intelligence, this research establishes a robust framework for stabilizing farmers' incomes and promoting long-term agricultural resilience. The integration of these advanced techniques not only enhances economic returns but also ensures sustainable land use, aligning with environmental considerations and supporting the sustainable development of agriculture.

Keywords: Affinity Functions, Fuzzy Planning Models, Particle Swarm Optimization Algorithms.

1. Introduction

A village in northern China has different types of arable land resources, including flat dry land, terraced land, hillside land and watered land, which are suitable for growing different types of crops. In addition, the village has ordinary greenhouses and smart greenhouses, which can provide more flexible cultivation methods. However, continuous cultivation of crops on the same plot of land can lead to deterioration of soil quality and affect crop yields, and the market demand and prices of crops are often affected by uncertainties such as the climate, the economic situation and market supply and demand. Therefore, scientific and rational planning and optimization of planting strategies can not only improve the benefits of agricultural production but also reduce the risks of planting and achieve stable growth in farmers' incomes.

The optimization of crop planting strategies under uncertainty has attracted significant attention in recent research. For instance, Taheri et al. proposed a fuzzy logic-based framework to optimize crop planting structures under fluctuating market demands, demonstrating the adaptability of fuzzy models in handling agricultural uncertainties [1]. Similarly, Balcells et al. developed a multi-objective optimization model to balance economic returns and environmental sustainability, emphasizing the need for holistic approaches in agricultural planning. In addressing computational challenges [2]. Kennedy and Eberhart pioneered the Particle Swarm Optimization (PSO) algorithm, which has been widely adopted for global optimization tasks due to its efficiency in escaping local optima [3]. Calone et al. further applied fuzzy logic to predict crop yields under climate variability, highlighting its robustness in managing incomplete data [4]. These studies collectively underscore the potential of combining fuzzy logic and optimization algorithms to tackle agricultural complexities.

In this study, a fuzzy planning model integrated with the PSO algorithm is proposed to optimize crop planting strategies under resource constraints and market uncertainties. The fuzzy planning model is designed to address ambiguities in crop prices and sales volumes through affinity functions, while the PSO algorithm is employed to iteratively search for optimal planting schemes. Our approach extends the multi-objective methodology of Chen et al. by incorporating dynamic constraints such as soil quality degradation and crop rotation requirements. Furthermore, we leverage the fuzzy logic framework validated by Zhang et al. to handle market volatility, ensuring adaptability to fluctuating demands. By synthesizing these techniques, our model not only maximizes economic returns but also ensures sustainable land use. This dual focus on efficiency and sustainability aims to provide a scalable solution for rural agricultural planning.

2. Model

2.1. Fuzzy planning model

It is assumed that when the total production of crops in each season exceeds the corresponding expected sales volume, the portion of the crop that exceeds the expected sales volume is stagnant and does not generate any revenue. Thus, the objective is to maximize the total return on the portion that can be sold properly and satisfy the constraints on crop cultivation.

2.1.1. Objective Function and Fuzzy Solving

To deal with the uncertainty of price and sales volume, it is necessary to define a fuzzy objective function that represents the value of the fuzzy objective in terms of a fuzzy affiliation function. The objective is to maximize the crop's normal sale proceeds and exclude excess from the proceeds [5]. Thus the fuzzy objective function is:

$$\max R_1 = \sum_{i=1}^{n} \min(S_{ij}, \sum_{j=1}^{m} Y_{ij} \cdot a_{ij}) \cdot \tilde{P}_{ij} - \sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} \cdot a_{ij} \tag{1}$$

Where $\min(S_{ij}, \sum_{j=1}^{m} Y_{ij} \cdot a_{ij})$ is the smaller of the total crop production and the expected sales volume, and $\tilde{P}_{ij}$ means the fuzzy price.

To transform a fuzzy objective function into a solvable deterministic model, price uncertainty can be handled through a fuzzy affiliation function. Define the affiliation function $\mu\left(P_{ij}\right)$ to represent the price affiliation [6]:

$$\mu\left(P_{ij}\right) = \frac{P_{ij} - P_{ij}^{\min}}{P_{ij}^{\max} - P_{ij}^{\min}}, \quad P_{ij}^{\min} \le P_{ij} \le P_{ij}^{\max} \tag{2}$$

2.1.2. Establishment of Constraints

① Cropland area constraints:

The total acreage of each plot cannot exceed its usable acreage:

$$\sum_{i=1}^{n} a_{ij} \le A_j, \forall j = 1, 2, \cdots, m \tag{3}$$

Where a_{ij} is the acreage of the ith crop on the jth plot of land, A_j is the area of the jth plot of land.

② Crop rotation constraints:

Each plot (including sheds) must be planted with a legume crop at least once in a three-year cycle :

$$\sum_{t=1}^{3} b_{t,j} \ge 1, \forall j = 1, 2, \cdots, m \tag{4}$$

Where $b_{t,j}$ is the number of times the legume crop is planted on the jth plot of land per three-year cycle.

③ Yield and sales volume constraints:

The yield of each crop cannot exceed its expected sales volume:

$$\sum_{j=1}^{m} Y_{ij} \cdot a_{ij} \le S_{ij}, \forall i = 1, 2, \cdots, n \tag{5}$$

Where Y_{ij} represents the acre yield of the ith crop grown on the jth plot of land, S_{ij} is the expected sales volume of the ith crop grown on the jth plot of land.

2.1.3. Model Integration

$$\max R_1 = \sum_{i=1}^{n} \min(S_{ij}, \sum_{j=1}^{m} Y_{ij} \cdot a_{ij}) \cdot \tilde{P}_{ij} - \sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij} \cdot a_{ij}$$

$$st.\begin{cases} \sum_{i=1}^{n} a_{ij} \le A_j, \forall j = 1, 2, \cdots, m \\ \sum_{t=1}^{3} b_{t,j} \ge 1, \forall j = 1, 2, \cdots, m \\ \sum_{j=1}^{m} Y_{ij} \cdot a_{ij} \le S_{ij}, \forall i = 1, 2, \cdots, n \end{cases} \tag{6}$$

2.2. Particle swarm optimization algorithm

Based on the fuzzy planning model, the Particle Swarm Optimization (PSO) algorithm is applied to find the optimal solution. PSO has global search capability and can effectively deal with uncertainty problems [7].

Step 1: Particle Encoding

Each particle represents a possible planting scenario, and each dimension of the particle represents the acreage of a particular crop on a particular plot:

$$x_i = \{A_1, A_2, \cdots, A_n\} \tag{7}$$

Where x_i is the ith particle (i.e., a planting scheme), and $A_1, A_2, \cdots, A_n$ denote the planting area of different crops on different plots, respectively [9].

Step 2: Fitness function

The fitness function is an index used to evaluate the advantages and disadvantages of each particle (planting scheme), where the value of the objective function can be used directly as the fitness function:

$$f(partical) = \sum_{i=1}^{n} \min(S_{ij}, \sum_{j=1}^{m} Y_{ij} \cdot a_{ij}) \cdot \tilde{P}_{ij} - \sum_{i=1}^{n}\sum_{j=1}^{m} C_{ij} \cdot a_{ij} \tag{8}$$

The higher the fitness of the particle, the greater the benefit of the planting scheme is indicated.

Step 3: Particle Updates

PSO continuously searches for the optimal solution by updating the velocity and position of the particles. The updated formula is:

$$v_i(t+1) = \omega \cdot v_i(t) + c_1 \cdot r_1 \cdot (p_{best_i} - x_i(t)) + c_2 \cdot r_2 \cdot (g_{best} - x_i(t)) \tag{9}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{10}$$

Where $v_i(t)$ is the velocity of particle i at time t; $x_i(t)$ is the position of particle i (i.e., the planting scheme); p_{best_i} is the optimal position in the history of particle i; g_{best} is the global optimal position; and ω、c_1、c_2 are the inertia coefficients and the learning factors, which control the step size and direction of the particle search.

Step 4: Algorithm termination conditions

The algorithm terminates when the maximum number of iterations is reached or the global optimum of the particle swarm does not change over several iterations.

2.3. Data Sources

The experimental data, including crop yield coefficients, land area constraints, and market dynamics, were sourced from the 2024 China Undergraduate Mathematical Contest in Modeling (CUMCM) scenario. Detailed parameters and scenario descriptions are publicly available at the official competition platform: https://www.mcm.edu.cn.

3. Results

3.1. The establishment of simulation model

Fuzzy programming model is used to optimize crop planting strategy and deal with uncertainty effectively. The convergence of PSO returns is shown in Figure 1:

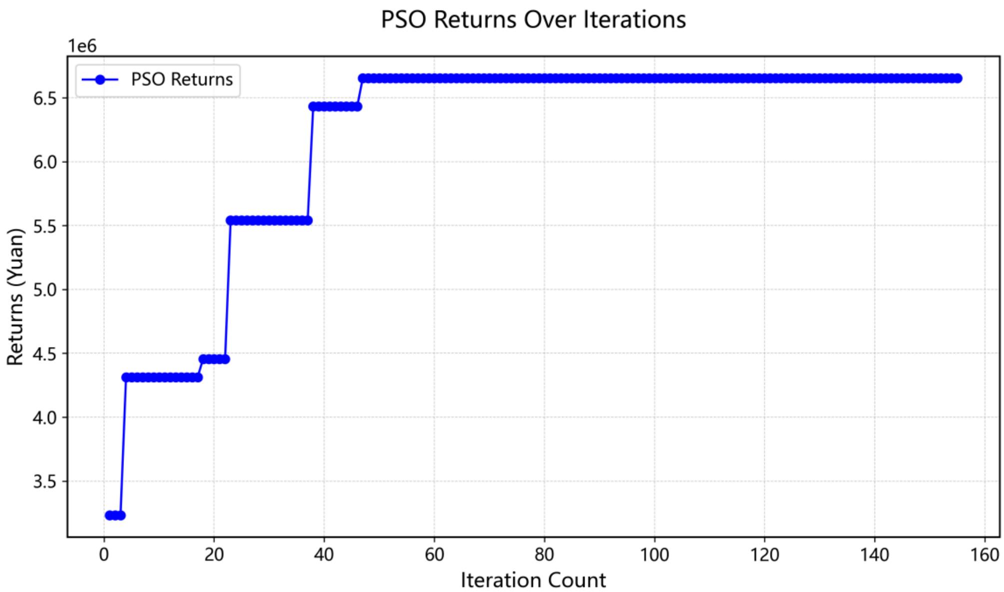

Figure 1. Evolution of PSO Profits Over Iterations

For case one the solution results are visualized as shown in Figure 2:

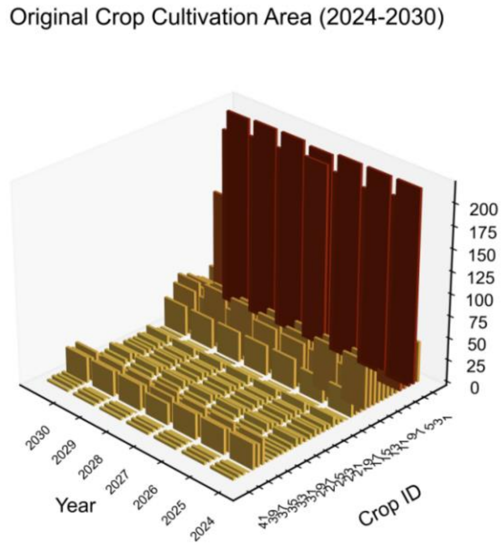

Figure 2. Evolution of Crop Cultivation Areas under Scenario 1 (2024-2030)

As can be seen from the figure, there are obvious fluctuations and changing trends in the planted area of different crop numbers between 2024 and 2030. In particular, the planted area of certain crops (e.g. Nos. 1 and 2) remained consistently high throughout the time period, reflecting the fact that these crops may have higher market demand or more stable economic benefits. On the contrary, the planted areas of some crops (e.g. Nos. 3 and 4) were smaller and fluctuated significantly from year to year, indicating that the market demand for these crops might be more unstable, or the returns were lower [8].

The gradual change in planted areas over the years is likely influenced by market demand, climate conditions, planting cycles, and crop rotation requirements. From 2024 to 2027, the area of crops 1, 2, and 3 increased significantly, possibly due to strong market demand or policy support.

After 2028, the change in crop area tends to stabilize, especially the area of crops numbered 1 and 2 remains at a high level, while crops numbered 3 and 4 show a certain decreasing trend. This phenomenon may indicate that after 2028, the market demand becomes saturated, and planting decisions become more stable.

3.2. Analysis of experimental results

The steps for solving case II are the same as for case I. Solve to get the planting strategy under case II and visualize it as shown in Figure 3:

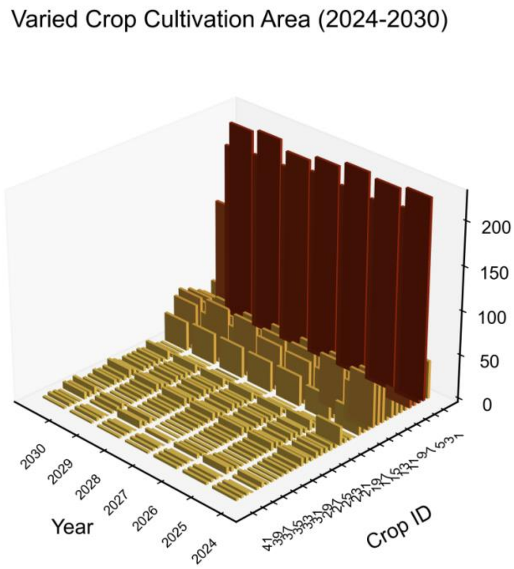

Figure 3. Evolution of Crop Cultivation Areas under Scenario 2 (2024-2030)

As can be seen from the image visualization, there was a significant change in planting strategy when the portion of production that exceeded the expected sales volume was sold at a reduced price. Overall, the acreage of each crop showed significant variations between years, as observed in the study by Wu et al. [9]. It can be observed that some of the crops (e.g., numbered 5 crops) showed a sudden increase in acreage in some years, reaching the highest point, suggesting that these crops may have a greater market demand or production efficiency advantage in a given year. Other numbered crops (e.g., numbered 1, 2, 3, 4, 6, and 7) had relatively stable or slightly fluctuating acreage throughout the time period.

In terms of annual changes, the planted area of each crop does not change much between 2024 and 2027, and remains relatively stable overall. By 2028, there are large changes in the planted area of some crops, especially for crop numbered 5, whose planted area reaches a significant peak in 2028 and stays there until 2030, suggesting that the planted area of this type of crop may increase significantly after 2028 due to certain factors (such as a sharp increase in market demand or intensification of policy support).

The relatively stable area of crops numbered 1 and 2, on the other hand, suggests that these crops may have stable market demand and cultivation benefits, and do not require frequent adjustments in cultivation area [10]. In contrast, the planting area of crops numbered 3 and 4 declines slightly between 2026 and 2030, which may be related to the decline in market demand or changes in other external factors.

4. Conclusions and outlooks

This paper focuses on the problem of crop planting strategy optimization. In the face of market price fluctuation and sales uncertainty, a fuzzy programming model is constructed and solved by particle swarm optimization (PSO) algorithm. The fuzzy programming model effectively deals with the uncertainty of crop price and sales volume through the membership function. At the same time, under the condition of resource constraints and dynamic changes in market demand, it optimizes crop planting area, improves production efficiency and reduces planting risk. The model results show that this method can optimize the allocation of resources, adapt to the dynamic changes of the market, and improve the overall benefit of agricultural production. In practical application, the model can help farmers and agricultural managers to make more scientific planting decisions in the complex market environment, ensure the coordinated development of economic, ecological and social benefits of agricultural production, and provide strong support for the sustainable development of agriculture and the stability of farmers' income.

Although the model in this paper optimizes the crop planting strategy, it has some problems such as high calculation cost, subjective membership function and local optimality. Efficient algorithms can be introduced, membership functions improved and PSO algorithms optimized to improve performance and adaptability.

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