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OPTIMIZING CROP PLANTING PLANS BASED ON GENETIC ALGORITHMS

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Abstract: With the expansion of agricultural production scale and diversification of market demands, scientific and rational crop planting planning is of great significance for improving agricultural production efficiency. This study aims to optimize crop planting plans using genetic algorithms to solve this complex multi-dimensional decision problem. The research establishes an optimization model with profit maximization as the objective, considering multiple constraints including land type restrictions, crop rotation requirements, and crop distribution. Two sales scenarios were designed: unsalable when exceeding expected sales volume (Scenario 1) and selling at half price (Scenario 2). Through an improved genetic algorithm utilizing multi-matrix chromosome coding, the study effectively handles multi-dimensional decision variables involving plots, years, seasons, and crops. Results show that Scenario 2 yields significantly higher profits (1.4×10^7 yuan) compared to Scenario 1 (2.9×10^6 yuan). In terms of crop yield distribution, cowpea, sword bean, kidney bean, potato, and tomato rank as the top five; regarding cultivated land area distribution, dry land shows the highest utilization rate, indicating its superior economic benefits. This study provides a practical decision-support tool for agricultural production planning.
Keywords: Crop planting plan, Genetic algorithm, Multi-Matrix chromosome coding, Profit maximization

1 INTRODUCTION

With the continuous growth of the world population and the increasing scarcity of agricultural resources, how to maximize agricultural output and economic benefits under limited land resources has become an urgent problem to be solved[1-2]. The challenge is further complicated by climate change and environmental degradation, which pose additional constraints on agricultural production systems. Traditional crop planting plans mainly rely on farmers' experience and intuition, lacking systematicity and scientificity, which makes it difficult to adapt to the needs of modern agricultural development[3]. Moreover, these conventional approaches often fail to consider complex interactions between multiple factors such as market demand, resource availability, and environmental conditions. In this context, it is particularly important and urgent to guide agricultural production and optimize crop planting plans by using modern optimization theory and methods.

In recent years, with the rapid development of artificial intelligence technology, intelligent optimization algorithms represented by genetic algorithms have attracted more and more researchers' favor due to their excellent global search ability and wide adaptability[4-6]. These algorithms have demonstrated remarkable potential in handling complex, multi -objective optimization problems that characterize modern agricultural planning. Genetic algorithms can efficiently search for optimal solutions by simulating natural selection and genetic mechanisms in biological evolution processes and have achieved many results in the field of agricultural decision optimization[7]. The ability to simultaneously consider multiple constraints and objectives makes them particularly suitable for agricultural planning problems, where various factors such as water availability, soil conditions, and economic considerations must be balanced. This study aims to use a genetic algorithm, an intelligent optimization tool, to model and optimize crop planting strategies under different scenarios, to provide scientific decision-making references for agricultural production, and to improve the efficiency of agricultural resource utilization and farmers' income.

2 DETERMINING THE OBJECTIVE FUNCTION AND CONSTRAINTS

The data in this paper originates from http://www.mcm.edu.cn. Before model building, the selected data undergoes preprocessing, including handling missing values through linear interpolation, detecting and removing outliers identified through box plots, and conducting correlation analysis and multicollinearity tests. Data from Appendices 1 and 2 on different crops' seasonal prices, costs, sales, and yields are integrated into a single table using Python to facilitate subsequent analysis and optimization of crop planting plans.

This section will use the optimization model to design and analyze the planting plan of crops in the region. First, this study need to determine the objective function. Assume that $x_{l,y,s,a}$ is represented by the area of l crops a planted in the plot in the year y season s. The objective function is to maximize the profit brought by the crop planting plan from 2024 to 2030. Assume that income is the income brought from 2024 to 2030, and cost represents the cost required for the crop planting strategy from 2024 to 2030. Then this paper has:

$$income = \sum_{y}\sum_{s}\sum_{a}\left(price_{y,s,a} * \sum_{l} x_{l,y,s,a}\right) \quad (1)$$

$$cost = \sum_{y}\sum_{l}\sum_{a}\sum_{s} c_{l,y,s,a} * x_{l,y,s,a} \quad (2)$$

Among them, $price_{y,s.a}$ represents the selling price of crop a in the sth season of year y, and $c_{l,y,s.a}$ represents the cost of crop a in the sth season of year y.

To make this study closer to the real situation, this study assumes two scenarios here: Situation 1 is unsalable when the expected sales volume is exceeded, and Situation 2 is sold at half price when the expected sales volume is exceeded. Two modes are set in the process of programming. One is that when the supply-market gap is greater than 0, the excess income is recorded as 0; the other is that when the supply-market gap is greater than 0, the price of the excess agricultural products is sold at half of the price in 2023.

Assume profit is Z, profit = revenue - cost, then:

$$\max\ Z = income - \cos t = \sum_{y}\sum_{s}\sum_{a}(price_{y,s,a} * x_{y,l,s,a}) - \sum_{y}\sum_{l}\sum_{a}\sum_{s}(c_{l,y,s,a} * x_{l,y,s,a}) \quad (3)$$

Let's start setting constraints. Assume that the set corresponding to arid land is A, the set corresponding to terraces is B, the set corresponding to hillside land is C, the set corresponding to irrigated land is D, the set corresponding to ordinary greenhouses is E, and the set corresponding to smart greenhouses is F, where $A = \{A_1, A_2, ..., A_6\}$ $B = \{B_1, B_2, ...B_{14}\}$ $C = \{C_1, C_2, ...C_6\}$ $D = \{D_1, D_2, ...D_8\}$ $E = \{E_1, E_2, ...E_{16}\}$ $F = \{F_1, F_2, ...F_4\}$. They will be described separately below.

Flat dry land, terraced fields, and hillside land can only grow one crop per year, irrigated land can grow one or two crops per year, and greenhouses can keep warm to a certain extent, so two crops can be grown per year.

$$\begin{cases} s \le 1, if\, l \in \{\mathrm{A,B,C}\} \\ s \le 2, else \end{cases} \quad (4)$$

Irrigated land can be used to grow rice in one season or vegetable crops in two seasons each year.

$$\begin{cases} s \le 1, if\ a \in \{16\} \\ \quad s \le 2, else \end{cases}, l \in \{\mathrm{D}\} \quad (5)$$

There are certain restrictions on the types of crops that can be grown on flat dry land, terraced fields, and hillsides.

$$\begin{cases} x_{l,y,s,a} \ge 0, if\ l \in \{\mathrm{D,E}\}, \mathrm{S} = 1 \\ x_{l,y,s,a} \ge 0, if\ l \in \{\mathrm{F}\} \\ x_{l,y,s,a} = 0, else \end{cases} \quad (6)$$

Represents the restrictions on the types of crops planted in the first season of irrigated land, the first season of ordinary greenhouses, and the first and second seasons of smart greenhouses.

$$\begin{cases} x_{l,y,s,a} \ge 0, if\, l \in \{\mathrm{A,B,C}\} \\ a \in \{1, 2, ..., 15\} \\ x_{l,y,s,a} = 0, else \end{cases} \quad (7)$$

The types of crops that can be planted in the second season of irrigated land are limited to vegetables.

$$\begin{cases} x_{l,y,s,a} \ge 0, if\ l \in \{\mathrm{D}\}, \mathrm{s} = 2 \\ x_{l,y,s,a} = 0, else \end{cases} \quad (8)$$

Ordinary greenhouses are suitable for growing one season of vegetables and one season of edible fungi each year, while smart greenhouses are suitable for growing two seasons of vegetables each year.

$$\begin{cases} x_{l,y,z,a} \ge 0, if\ l \in \{\mathrm{E}\}, s = 2 \\ x_{l,y,z,a} = 0, else \end{cases} \quad (9)$$

Each crop cannot be planted continuously on the same plot of land (including the greenhouse).

$$\begin{cases} x_{l,y,s,a} + x_{l,y+1,s,a} \le 1, ifs \le 1 \\ x_{l,y,1,a} + x_{l,y,2,a}\ or\ x_{l,y,2,a} + x_{l,y+1,1,a}, else \end{cases} \quad (10)$$

All land in each plot (including greenhouses) is planted with legumes at least once in three years.

$$\sum_{i=0}^{2} x_{l,y+i,s,a} \geq 1, a \in \{1,2,3,4,5,17,18,19\} \tag{11}$$

The above formula means that the planting area of each crop in each season cannot be too scattered. In this paper, the constraint is that a crop can only be planted on 4 pieces of arable land at most during the same period. Then there is:

$$\sum_{l} x_{l,y,s,a} \leqslant 4 \tag{12}$$

The area of each crop planted in a single plot (including greenhouses) should not be too small, and the area planted in a single plot (including greenhouses) should not be less than 20% of the land.

$$x_{l,y,s,a} > 0.2 * A_l \tag{13}$$

The total area under crop cultivation cannot exceed the area of arable land.

$$\sum_{p} x_{l,y,s,a} \leq A_l \tag{14}$$

Among them, A_l represents the total area of cultivated land l.

3 SOLVING CROP PLANTING PLANS UNDER TWO OPTIMIZATION SCENARIOS USING GENETIC ALGORITHMS

Genetic Algorithms (GA) are search algorithms that mimic natural selection and genetic principles. GA encodes potential solutions as "individuals" in a "population." The population evolves through selection, crossover (mating), and mutation operations to find optimal or satisfactory solutions. GA performs a global search, avoiding local optima. Its simple structure adapts to various problems by adjusting genetic operations and parameters[8].

The process initializes a random population, then iteratively evaluates fitness, selects high-fitness individuals, performs crossover and mutation to generate new individuals, and continues until termination criteria are met. This optimization process aims to find the best or satisfactory solutions[9].

In this study, the decision variables $x_{l,y,s,a}$ involved different plots, years, seasons, and crops. It is a multi-dimensional dynamic variable that is difficult to represent using traditional coding methods. Therefore, this study improved the GA algorithm and adopted multi-matrix chromosome coding, which can more naturally map complex decision variables involving multiple dimensions such as plots, years, seasons, and crops[10]. This coding method facilitates the genetic algorithm to perform operations such as crossover and mutation. By distributing the decision variables in different matrices, not only decomposes the original huge search space into multiple small spaces but also improves the pertinence and efficiency of the search. Each matrix focuses on processing one type of decision variable, making the genetic algorithm more flexible and helping to find the optimal solution more effectively.

In summary, the model parameter settings of this paper are shown in Table 1:

Table 1 The Recommended Fonts

Parameter	Value
Iterations	1000
Crossover rate	0.8
Mutation rate	0.2
Population size	30

The convergence curve of the model in situation 1 is shown in Figure 1, and the convergence curve of the model in situation 2 is shown in Figure 2.

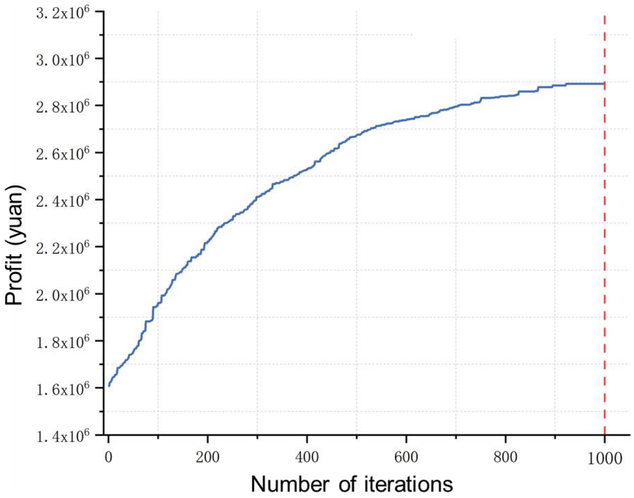

Figure 1 Situation 1 Convergence Curve

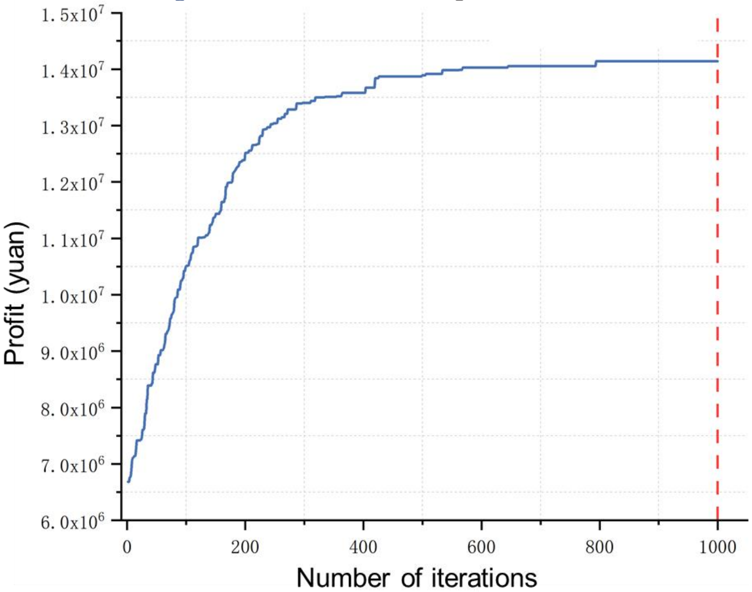

Figure 2 Situation 2 Convergence Curve

In scenario 1, after around 900 iterations, the convergence curve stabilizes at approximately 2.9106, indicating a profit of 2.9106 yuan. In scenario 2, the curve stabilizes after about 600 iterations at around 1.4107, suggesting a profit of 1.4107 yuan. Both scenarios converge quickly to optimal solutions, but scenario 2 achieves significantly higher profits (1.4107 vs 2.9106 yuan), demonstrating its superior sales strategy and revenue potential.

Due to space limitations, only the crop yield distribution and cultivated land area distribution of Case 2 are shown here, as shown in Figures 3 and 4.

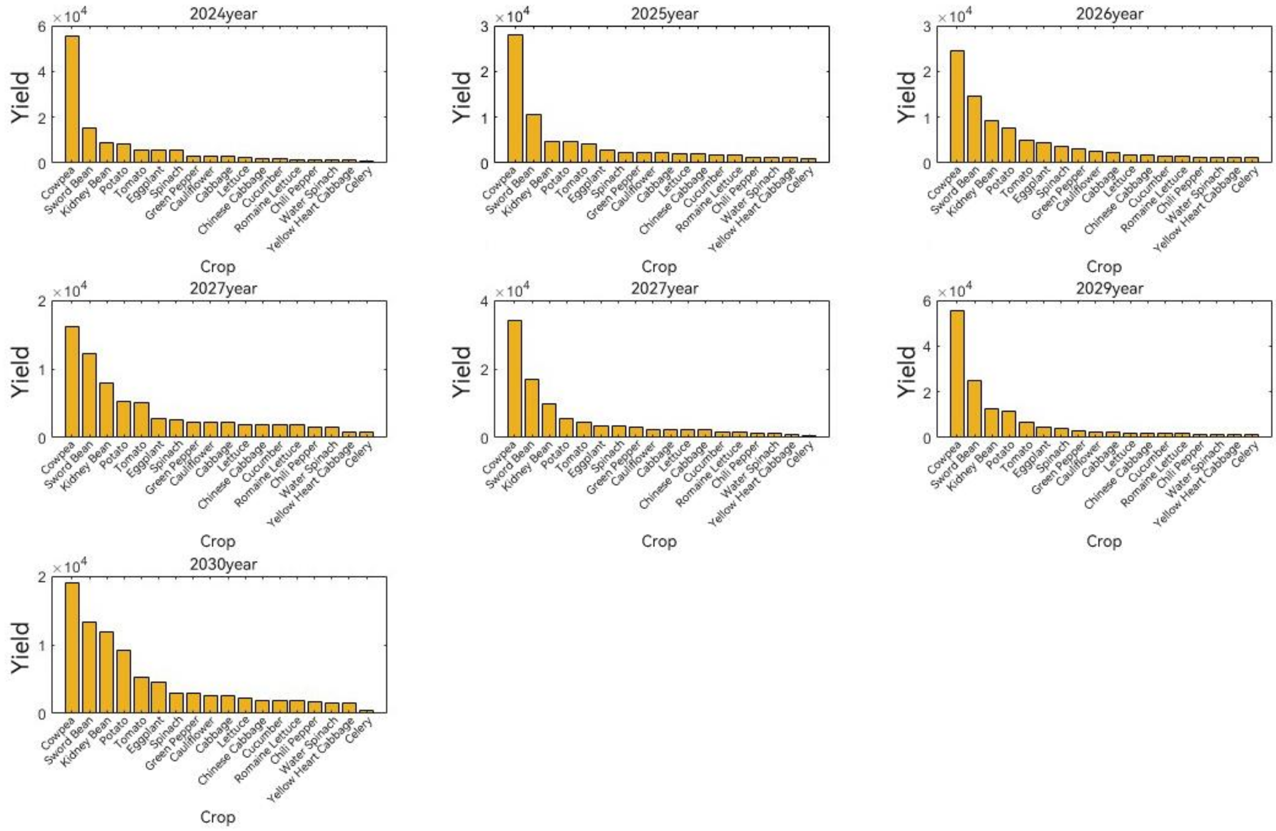

Figure 3 Scenario 2 Distribution of Crop Yields

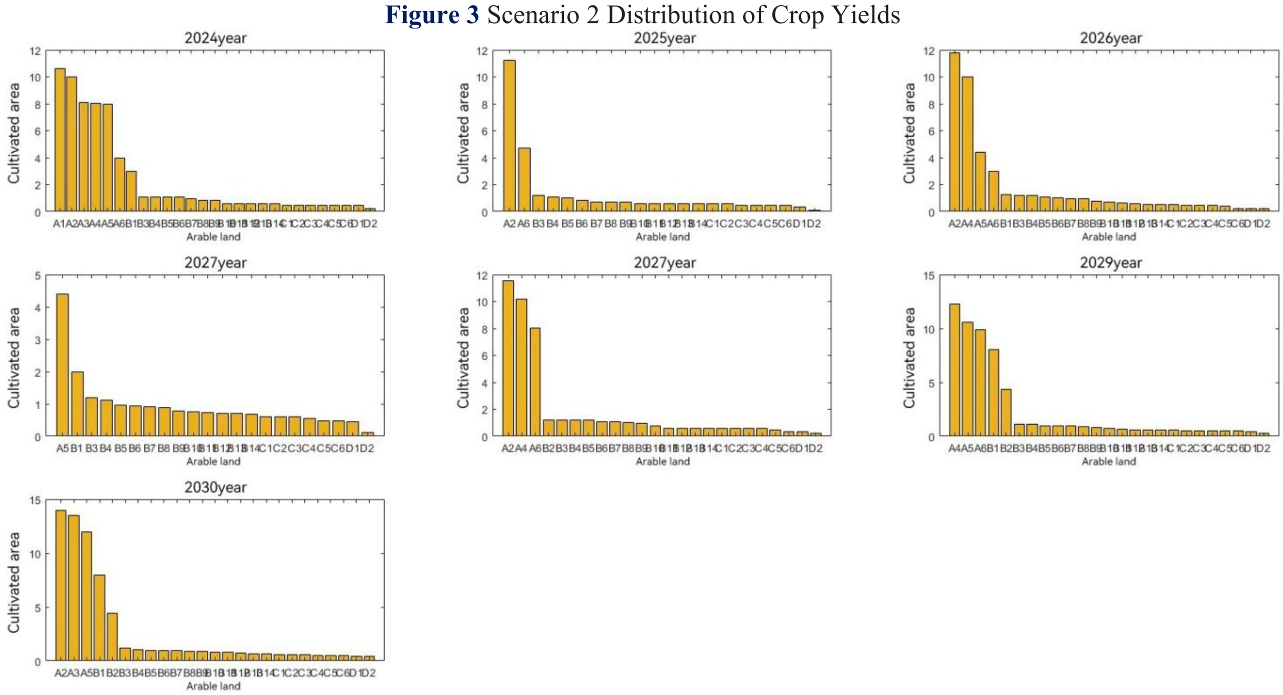

Figure 4 Scenario 2 Distribution of Cultivated Land Area

As can be seen from the above figure, in both case (1) and case (2), the top five crops in terms of crop yield are cowpea, sword bean, kidney bean, potato, and tomato, indicating that the economic benefits of these five crops are often good, so the yield is relatively large. In case (1), the top five cultivated land areas are all Class A land, that is, arid land; in case (2), the top five cultivated land areas include both Class A land and Class B land (arid land and terraced fields), indicating that overall, regardless of case (1) or case (2), the utilization rate of arid land in the planting plan is high, which indirectly reflects that the economic benefits brought by arid land are high.

4 CONCLUSIONS

This study developed an optimized crop planting strategy model using genetic algorithms, comparing scenarios where excess produce is either unsalable or sold at half price. The improved genetic algorithm with multi-matrix chromosome coding demonstrated effective convergence, with the half-price scenario achieving significantly higher profits. The analysis revealed that certain crops, notably cowpea, sword bean, kidney bean, potato, and tomato, consistently showed superior economic performance, while arid land emerged as the most economically advantageous cultivation area. These findings provide valuable insights for agricultural planning, suggesting that flexible pricing strategies combined with optimal crop selection can substantially enhance agricultural profitability. However, the current model has limitations, including its reliance on historical data without considering potential climate change impacts and market volatility. Future research could enhance this work by incorporating weather prediction models, market trend analysis, and the impact of emerging agricultural technologies. Additionally, the model could be expanded to consider environmental sustainability metrics and social factors affecting agricultural communities.

CONFLICT OF INTEREST

The authors have no relevant financial or non-financial interests to disclose.

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