Research On Rational Organic Farming Practices Based on A Multifactor Optimization Model Using Genetic Algorithm

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Abstract. Given the global population growth and the shrinking availability of arable land, it is crucial to adapt organic farming techniques to the specific characteristics of rural areas. This approach aims to maximize the utilization of available land and promote the economic development of rural communities. This paper introduces a multifactor optimization strategy to identify the most profitable agricultural farming practices. The model considers various factors, including seasonality, economic conditions, land suitability for planting, climate conditions, market prices, and planting costs. Additionally, it takes both the substitutability and complementarity of crop options into account. By employing a genetic algorithm (GA), the model is designed to identify the highest productivity planting schemes, addressing the complexity and multi-objective nature of agricultural planning. The results demonstrate that the proposed optimization strategy can significantly improve the sustainability and profitability of organic farming practices, enhancing the economic returns for farmers and contributing to the development of rural communities.

Keywords: Multi-objective Optimization Model, K-means Clustering Algorithm, Genetic Algorithm.

1. Introduction

As the global population grows and land resources become more constrained, optimizing organic farming practices in rural areas is crucial for maximizing arable land use and promoting sustainable economic growth. This manuscript, based on the data and constraints from the 2024 Chinese College Students Mathematical Modeling Competition Question C, develops a multifaceted optimization model to identify profitable cultivation strategies. It aims to balance environmental sustainability and economic prosperity through mathematical principles and a deep understanding of local conditions.

Existing research focuses on optimal planting strategies using intelligent optimization algorithms with multiple constraints. For instance, Xiao Liu (2021) [1] used a distributed AquaCrop model and a multi-objective genetic algorithm (NSGA-II) to create a rational irrigation schedule. Guiping Hu (2022) [2] developed a two-stage decision support system based on a 1D-CNN model and GDUs (Growing Degree Units) to optimize planting decisions, addressing weather variability and storage capacity.

This study extends these approaches by considering seasonal, economic, and land factors, including climate conditions, planting costs, market prices, and crop substitutability and complementarity. A multi-objective optimization model based on a genetic algorithm (GA) [3] is employed to determine the optimal planting strategy.

The methodology involves analyzing the impact of fluctuations in sales volume, yield, planting cost, and selling price on planting profits. Cost-effectiveness and risk index parameters are introduced. An economic analysis compares the cost-effectiveness of different crops, and the K-means clustering algorithm [4] categorizes crops into four types: high-yield high-risk, high-yield low-risk, low-yield high-risk, and low-yield low-risk.

A sales competition matrix is constructed to understand market interactions between crops. Finally, the multi-objective optimization model [5] integrates all these factors, with decision variables and constraints based on practical agricultural requirements. Two objective functions are formulated, incorporating sub-variables like profit, relative crop height, and plot distance. The genetic algorithm is used to solve for the optimal planting scheme, effectively handling the complexity and multiple objectives of this agricultural planning problem. The entire analysis process is described in Figure 1.

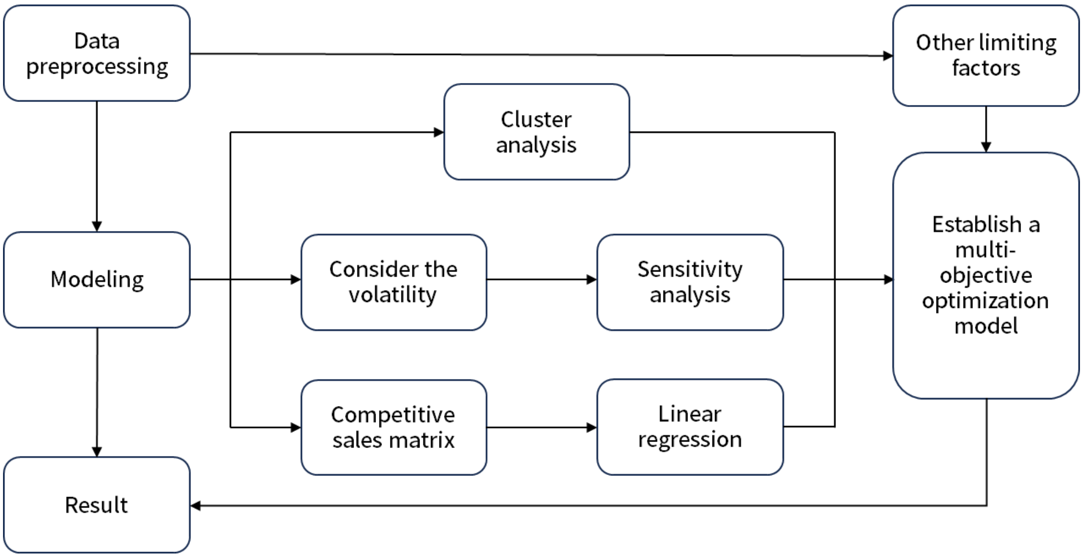


Figure 1 Full text flowchart

2. The fundamental of Genetic algorithms

Genetic algorithm (shown in Figure 2) is a heuristic algorithm based on the principles of natural selection and genetics, which can gradually optimize the solution to the problem by simulating the biological evolution process. Specifically, the genetic algorithm starts from the initial population, generates a new population through operations such as crossover and mutation, and uses the fitness function to evaluate the quality of the solution. Through continuous iteration, the algorithm gradually optimizes the quality of the solution and finally converges to the global optimal or approximately optimal solution.

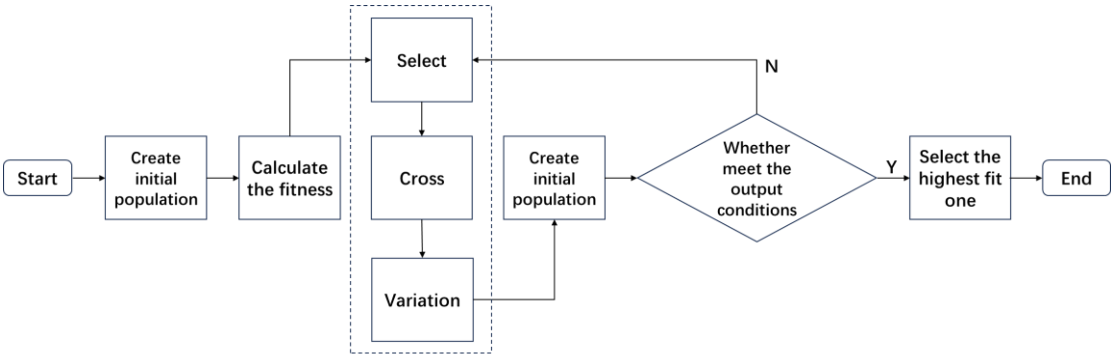


Figure 2 GA Process Flowchart

3. Results

3.1. Data preprocessing

The following analysis is conducted based on the data of Question C of the 2024 China National College Student Mathematical Modeling Contest. [https://www.mcm.edu.cn/upload_cn/node/725/pmkWxf8H9cfe9984c1a1a5b1263e5dd3b5596ed5.zip].

Introduce cost-effective parameter indicators λ_i and a risk index μ_i to evaluate the comprehensive benefits of various crops on a unit plot and volatility of a certain crop's unmalleability:

$$\lambda_i = w_{ijk}/s_{ijk} \tag{1}$$

Where w_{ijk} is profit per unit area of crop j planted on plot i in season k, and s_{ijk} is area of plot i planted with crop j in season k.

$$\mu_i = X_{ij} \cdot C_{ijk} \Big/ \sum_{1 \leqslant i \leqslant 54} X_{ij} \cdot C_{ijk} \tag{2}$$

Where w_{ijk} is profit per unit area of crop j planted on plot i in season k, and s_{ijk} is area

Where X_{jk} is market demand (expected sales volume) for crop j in season k, and C_{ijk} is cost per unit area of planting crop j on plot i in season k.

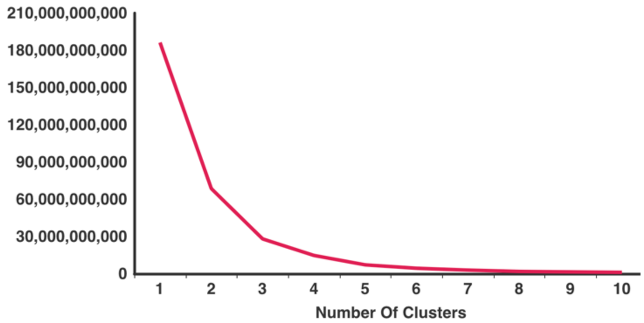


Figure 3 Cluster effect analysis

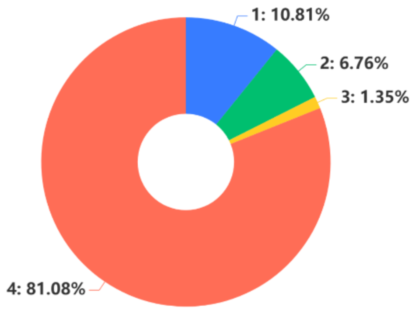


Figure 4 Cluster proportion distribution

Apply K-means cluster analysis method to construct a crop classification model based on economic indicators such as crop yield per mu, planting cost, market unit price, cost performance parameters, risk index, etc.

According to the elbow rule, that is, the inflection point in Figure 3 is the recommended cluster number, different types of crops are divided into four categories: high return and high risk, high return and low risk, low return and high risk, and low return and low risk, as shown in Figure 4. Table 1 qualitatively compares the basic planting information of the four categories of crops.

Table 1 Distribution of Cluster Center Coordinates

Cluster Type	Sales Price Center Value	Yield per Acre Center Value	Risk Coefficient Center Value	Cost-Effectiveness Parameter Center Value	Maximum Profit Center Value	Minimum Profit Center Value
1	17.5	2110.8	3142201	12.5	31860.6	22612.3
2	19.3	4360.0	63459214	7.5	63260.0	47840.0
3	27．0	2000.0	121894375	2.1	13000.0	8000.0
4	14.8	1731.2	23549217	3.8	35631.6	23539.7

From Table 2, through the evaluation indicators—silhouette coefficient, DBI, and CH, it can be judged that the results of this cluster analysis are good, and various crops have been successfully divided into four types.

Table 2 Evaluation Metrics of Clustering Effect

Silhouette Coefficient	DBI	CH
0.770	0.429	922.937

By consulting relevant literature to determine the relative height of plants, the differences in plant heights of different crops can be seen. Based on this problem, when planning, priority should be given to arranging plants of similar heights for planting on the same plot to reduce the number of plants of different heights. Growth competition among them prevents tall plants from blocking the light needs of short plants:

$$H = \frac{1}{41}\sum_{i}\sum_{j_1, j_2 \in j} {H_{j_1, j_2}}^2 \cdot M_{ijk} \tag{3}$$

Where M_{ijk} indicates whether crop j is planted on plot i in season k (1 if planted, 0 otherwise). H is the sum of the variance of the relative heights of different crops in all plots to ensure a high balance of crops in the same plot.

At the same time, assuming that the relative distance between different plots of the same type is 1, and the relative distance between different types of plots is 2, to simplify field management, limit the relative distance of the same crop and ensure that the crops are not too scattered in each season:

$$D = \frac{1}{54}\sum_{j}\sum_{i_1, i_2 \in i} {D_{i_1, i_2}}^2 \cdot M_{ijk} \tag{4}$$

D is the sum of the variances of the relative distances between different plots where the same crop is located.

3.2. Build a multi-objective optimization model

3.2.1 Define decision variables

Considering necessary constraints such as crops cannot be planted repeatedly and legumes need to be planted on the same plot at least once every three years, the 0-1 variable M_{ijk} [6] is proposed.

$$M_{ijk} = \begin{cases} 0, plot\ i\ was\ not\ planted\ with\ crop\ j\ in\ season\ k \\ 1, plot\ i\ was\ planted\ with\ crop\ j\ in\ season\ k \end{cases} \tag{5}$$

3.2.2 Establish constraints

In the case of joint planting, it is necessary to ensure that the total planting area of each plot of crops cannot exceed the actual planting area of the plot:

$$\sum_{1 \leqslant j \leqslant 41} s_{ijk} \cdot M_{ijk} \leqslant A_i, \quad i = 1, 2, 3, \cdots, 54;\ k = 1, 2, 3, \cdots, 16 \tag{6}$$

$$s_{ijk} \geqslant 0 \tag{7}$$

Where A_i is total area of plot i.

Long-term heavy stubble can lead to the accumulation of pests and diseases, soil nutrient imbalance, and reduced crop yield and quality. Therefore, it is necessary to avoid the continuous cultivation of certain crops:

$$\sum_{1 \leqslant k \leqslant 13, k \in odd} [M_{ijk} + M_{ij(k+1)}] \cdot [M_{ij(k+2)} + M_{ij(k+3)}] = 0 \tag{8}$$

Legume crops are grown to meet their own nitrogen needs, but also to provide additional nitrogen for other crops to be planted, reducing dependence on chemical fertilizers. They need to be planted in the same plot at least once every three years:

$$\sum_{1 \leqslant j \leqslant 5, 17 \leqslant j \leqslant 19}\ \sum_{1 \leqslant k \leqslant 6} M_{ijk} \geqslant 1, \quad i = 1, 2, 3, \cdots, 54 \tag{9}$$

As root crops, cabbage, white radish and carrot are usually suitable for planting in seasons with mild climate and large temperature difference between day and night to ensure that their roots are fully expanded and achieve higher quality and yield. Therefore, these crops are often planted in the second season of the year:

$$\sum_{35\leqslant j\leqslant 37}\sum_{1\leqslant k\leqslant 15, k\in odd} M_{ijk}=0 \tag{10}$$

Chinese cabbage, white radish and carrot have high requirements on soil moisture and water supply, so they are restricted to be grown only in irrigated fields:

$$\sum_{27\leqslant i\leqslant 50}\sum_{17\leqslant j\leqslant 34}\sum_{2\leqslant k\leqslant 16, k\in even} M_{ijk}=0 \tag{11}$$

Chinese cabbage, carrot and white radish have similar root growth patterns, and the peak demand for water and nutrients may overlap during the growth process, so only one of them can be planted in the same watered plot:

$$\sum_{1\leqslant i\leqslant 26, 35\leqslant i\leqslant 54}\sum_{35\leqslant j\leqslant 37} M_{ijk}=0 \tag{12}$$

$$k\in even\text{时，}\quad \sum_{27\leqslant i\leqslant 34}\sum_{35\leqslant j\leqslant 37} M_{ijk}\leqslant 1 \tag{13}$$

The growth conditions of edible fungi are relatively strict, and they are usually suitable for cultivation in milder seasons. Therefore, the cultivation of edible fungi is limited to the second season:

$$\sum_{38\leqslant j\leqslant 41}\sum_{1\leqslant k\leqslant 15, k\in odd} M_{ijk}=0 \tag{14}$$

The growth of edible fungi has strict requirements on environmental conditions. Ordinary greenhouses have good insulation, moisturizing and ventilation functions and are suitable for the cultivation of edible fungi. Therefore, edible fungi are restricted to be grown only in ordinary greenhouses:

$$\sum_{1\leqslant i\leqslant 50}\sum_{38\leqslant j\leqslant 41} M_{ijk}=0 \tag{15}$$

As a food crop with extremely high-water requirements, rice can usually only be grown in irrigated fields to ensure that its roots are always immersed in water during the entire growth process to meet its special growth needs:

$$\sum_{1\leqslant i\leqslant 26, 35\leqslant i\leqslant 54} M_{i,16,k}=0\text{，} \tag{16}$$

in contrast, other food crops except rice are relatively less dependent on water and are more suitable for cultivation in non-irrigated land environments such as flat dry land, terraces and hillside fields:

$$\sum_{27\leqslant i\leqslant 54}\sum_{1\leqslant j\leqslant 15} M_{ijk}=0 \tag{17}$$

As a crop with high sensitivity to environmental factors such as temperature, humidity and light, vegetables are suitable for cultivation in a variety of planting environments, whether it is traditional watering or modern smart greenhouses, can fully meet their growth needs:

$$\sum_{1\leqslant i\leqslant 26}\sum_{17\leqslant j\leqslant 34}\sum_{1\leqslant k\leqslant 16} M_{ijk}=0 \tag{18}$$

$$\sum_{27\leqslant i\leqslant 50}\sum_{17\leqslant j\leqslant 34}\sum_{2\leqslant k\leqslant 16,k\in even}M_{ijk}=0 \tag{19}$$

The coefficient of variation is a statistic that measures the relative dispersion of a data set and is used to evaluate whether the distribution of crop planting areas is balanced among different regions. A coefficient of variation of more than 10% in planting area is considered too scattered. To improve the convenience of production and management, it is usually required that the planting area of each crop in each season should not be too scattered:

$$when\ \bar{s}\neq 0,\quad \sqrt{\frac{\sum_{1\leqslant i\leqslant 54}(s_{ijk}-\bar{s}_{ijk})^2}{\sum_{1\leqslant i\leqslant 54}M_{ijk}}}\Bigg/\frac{\sum_{1\leqslant i\leqslant 54}s_{ijk}}{\sum_{1\leqslant i\leqslant 54}M_{ijk}}\leqslant 0.1 \tag{20}$$

To optimize resource allocation, maintain ecological balance and crop rotation system, the same crop can be planted in no more than 7 plots:

$$\sum_{1\leqslant i\leqslant 54}M_{ijk}\leqslant 7 \tag{21}$$

3.2.3 Simulate the fluctuations of variables in actual production

During the agricultural planting process, there are certain uncertainties and potential planting risks in the expected sales volume, yield per mu, planting cost and sales price of various crops. Therefore, the expected sales volume change factor α_{ijk}, yield per mu change factor β_{ijk}, and sales price change factor δ_{ijk} are introduced. According to the actual situation, the random numbers function of the NumPy library in Python is used to generate data of $\alpha_{ijk},\beta_{ijk}, and\ \delta_{ijk}$ that obeys the normal distribution.

(1) Fluctuating expected sales volume:

$$X_{jk}'=\frac{1-(-1)^k}{2}\cdot X_{j,k-2}\cdot(1+\alpha_{ijk})+\left[\frac{1+(-1)^k}{2}\right]\cdot X_{j,k-1}, \tag{22}$$

based on the expected average annual growth rate of wheat and corn sales between 5% and 10% and the expected future sales volume of other crops changing by 5% relative to 2023, the following can be obtained:

$$\alpha_{ijk}\in\begin{cases}[0.05,0.1],j=6\ or\ j=7\\ [-0.05,0.05],1\leqslant j\leqslant 5\ or\ 8\leqslant j\leqslant 41\end{cases} \tag{23}$$

(2) Fluctuating yield per mu:

$$R_{ijk}'=\left(\frac{1-(-1)^k}{2}\right)\cdot R_{ij,k-2}\cdot(1+\beta_{ijk})+\left[\frac{1+(-1)^k}{2}\right]\cdot R_{ij,k-1}, \tag{24}$$

Where R_{ijk} is yield per unit area of crop j planted on plot i in season k

The yield per mu of crops changes by $\pm 10\%$ every year due to the influence of climate and other factors:

$$\beta_{ijk}\in[-0.1,0.1] \tag{25}$$

(3) Fluctuating planting costs:

$$P_{ijk}{}'=\begin{cases} P_{ij,k-1}, 1\leqslant j\leqslant 16 \\ \left(\dfrac{1-(-1)^{k}}{2}\right)\cdot P_{ij,k-2}\cdot(1+0.05)+\left[\dfrac{1+(-1)^{k}}{2}\right]\cdot P_{ij,k-1}, 17\leqslant j\leqslant 37 \\ \left(\dfrac{1-(-1)^{k}}{2}\right)\cdot P_{ij,k-2}\cdot(1-\delta_{ijk})+\left[\dfrac{1+(-1)^{k}}{2}\right]\cdot P_{ij,k-1}, 38\leqslant j\leqslant 40 \\ \left(\dfrac{1-(-1)^{k}}{2}\right)\cdot P_{ij,k-2}\cdot(1-0.05)+\left[\dfrac{1+(-1)^{k}}{2}\right]\cdot P_{ij,k-1}, \quad j=41 \end{cases} , \tag{26}$$

Where P_{ijk} is price per unit area of crop j planted on plot i in season k

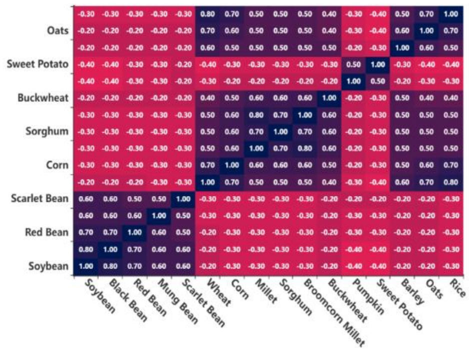
The sales prices of grain crops are stable, the average annual growth rate of vegetable sales prices is around 5%, the annual average sales price of edible fungi decreases by 1% to 5%, and the annual sales price of morels decreases by a larger rate of 5%:

$$\delta_{ijk}\in[-0.05, \quad -0.01] \tag{27}$$

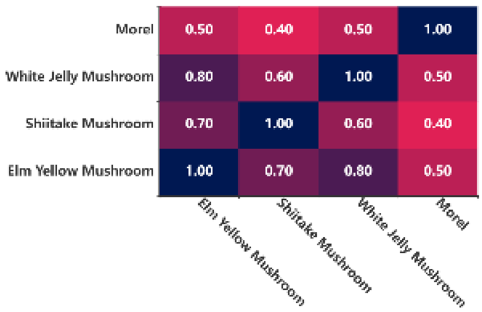
3.2.4 Consider the correlation between variables

In real life, there may be a certain degree of substitutability and complementarity between various crops [7], and there is also a certain correlation between expected sales volume, sales price, and planting cost.

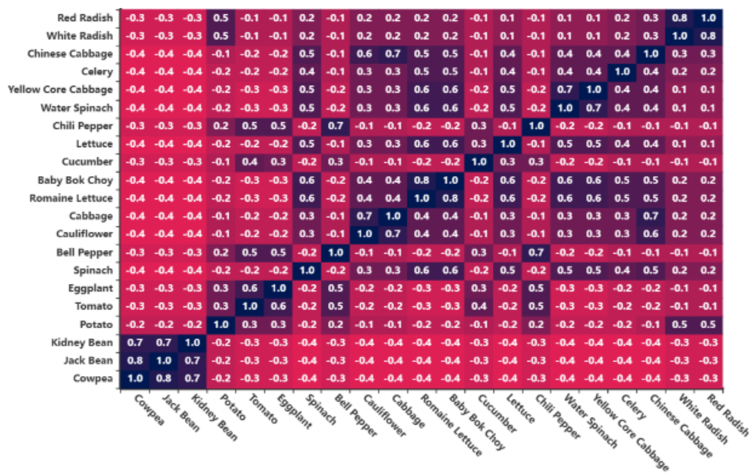
The substitution and complementary characteristics of crops are often affected by a combination of factors, including economic benefits, ecological environment, climate adaptability, nutritional value, market demand, planting technology and soil characteristics. The following is a sales competition matrix between crops based on the above factors. The value of this matrix ranges from -1 to 1, where positive values represent competitive relationships, negative values represent complementary or promotional relationships, and 0 represents neutral relationships.



(a) Crop Competition Matrixes



(b) Mushroom Competition Matrixes



(c) Vegetable Competition Matrixes

Figure 5 Crop, Vegetable and Mushroom Competition Matrixes

According to Figure 5, legume crops exhibit strong positive correlations (0.5-0.8) with each other, indicating a strong competitive relationship, while most show negative or weak correlations with cereals, reflecting their complementary nature (e.g., legumes can fix nitrogen, benefiting cereal growth). Cereal crops generally show moderately strong positive correlations (0.4-0.8), reflecting a clear competitive relationship. The tuber crop sweet potato has a negative correlation with most other crops, suggesting it has minimal competition and potential complementary effects. Legume vegetables also show strong positive correlations (0.7-0.8) with each other, indicating strong competition, and weak negative correlations with other vegetables, suggesting a slight complementary relationship. Solanaceous vegetables (tomatoes, eggplants, green peppers, capsicums) and leafy vegetables generally show moderate to strong positive correlations (0.4-0.8), reflecting significant competition. Root vegetables like potatoes, white radish, and carrots have a moderate positive correlation (0.5), indicating some competition, while white radish and red radish have a very high correlation (0.8), indicating the most obvious competition. Among fungi, Elm Yellow and White Jelly mushrooms show a strong competitive relationship (0.8), while Lentinus edodes and morels have relatively weak competition due to their unique qualities and high prices. All fungal correlations are positive, suggesting some degree of competition between them.

According to the above competition relationship matrix, the value of the competition parameter η can be obtained (different types of crops are regarded as 0), and then the corrected actual planting area can be obtained:

$$X''_{i,j_m,k} = X'_{i,j_m,k}\left(1 - \sum_{n} \eta_{j_m,j_n} \cdot \frac{X'_{i,j_n,k}}{\sqrt{\sum_{j} {X_{ijk}}^{2}}}\right) \tag{28}$$

Next, use the Pearson correlation coefficient to explore the correlation between expected sales volume, sales price, and planting cost.

By normalizing the expected sales volume, sales price, and planting cost, the impact of different scales and units is eliminated. For a random variable $\{X_i\}$, assuming that its skewness is S and kurtosis is K, construct the JB statistic [8]:

$$JB = \frac{n}{6}\left[S^2 + \frac{(K-3)^2}{4}\right] \tag{29}$$

It can be proved that if $\{X_i\}$ is a normal distribution, then in the case of a large sample, $JB \sim \chi^2(2)$,the steps for hypothesis testing are as follows:

(1) Propose the null hypothesis H_0: the random variable obeys a normal distribution.

(2) Put forward an alternative hypothesis H_1: the random variable does not obey the normal distribution.

(3) After constructing the statistic, obtain the p value and compare it with the significance level α (here 0.1).

As just described, it can be qualitatively concluded that the expected sales volume, sales price, and planting cost are in line with the normal distribution, and the Pearson correlation coefficient can be used for correlation test. The Pearson correlation coefficient is used below to measure the linear correlation between expected sales volume and planting cost, and between sales price and planting cost. It can be obtained from linear regression:

$$X_{jk} = 0.35C_{ijk} + 2654.39 \tag{30}$$

X_{jk} represents the expected sales volume, and C_{ijk} represents the planting cost, which can simplify the model.

3.2.5 Create objective function

When the total output of crops per season exceeds demand and the excess is unsalable, the total profit is:

$$W = \sum_{k_0 \leqslant k \leqslant k_0+1} P_{ijk}' \cdot \min\left(R_{ijk}' \cdot S_{ijk} \cdot M_{ijk},\quad X_{jk}'\right) \cdot C_{ijk}' \cdot S_{ijk} \cdot M_{ijk} \tag{31}$$

When the total output of crops per season exceeds demand and the excess is sold at a price reduction of 50% of the selling price in 2023, the total profit is:

$$W = \sum_{k=k_0}^{k_0+1} \begin{matrix} \dfrac{1-\operatorname{sgn}\left(R_{ijk}' \cdot S_{ijk} \cdot M_{ijk} - X_{jk}'\right)}{2}\left(P_{ijk}' \cdot \sum\limits_{1 \leqslant i \leqslant 54} R_{ijk}' \cdot S_{ijk} \cdot M_{ijk} - C_{ijk}' \cdot S_{ijk} \cdot M_{ijk}\right) + \\ \dfrac{1+\operatorname{sgn}\left(R_{ijk}' \cdot S_{ijk} \cdot M_{ijk} - X_{jk}'\right)}{2}\left[0.5 \times P_{ijk}' \cdot \left(\sum\limits_{1 \leqslant i \leqslant 54} R_{ijk}' \cdot S_{ijk} \cdot M_{ijk} + X_{jk}'\right) - C_{ijk}' \cdot S_{ijk} \cdot M_{ijk}\right] \end{matrix} \tag{32}$$

3.3. Apply genetic algorithm to calculate maximum profit

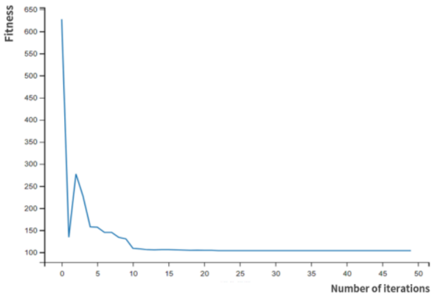


Figure 6 GA fitness curve

Figure 6 shows the fitness curve [9] of our genetic algorithm during training. After multiple verifications, the number of evolutions was selected to be 50, the crossover probability was 0.4, the mutation probability was 0.1, and the sample size was 100. According to the changes in the fitness curve, it can be known that the fitness curve of the genetic algorithm shows obvious fluctuations in the early stage of evolution (the first 5 generations). This kind of fluctuation is mainly due to the large randomness of the initial population, the large fitness differences of individuals, and the continuous introduction of new gene combinations by crossover and mutation operations, resulting in strong fitness fluctuations in the population. As the iteration of the genetic algorithm proceeds, the fitness curve gradually becomes stable after the 10th generation. This shows that most individuals in the population are close to the optimal solution currently, the algorithm gradually converges to the global optimal solution, and the volatility weakens [10].

4. Conclusions

The multi-objective optimization model developed in this study effectively integrates various factors, including crop yield, planting cost, market unit price, cost-effectiveness parameters, and risk index, to optimize crop planting strategies for the years 2024-2030. The model sets practical constraints, such as avoiding consecutive planting of the same crop, ensuring legume crops are planted at least once every three years on the same plot, and preventing excessive dispersal of the same crop. Using a genetic algorithm (GA), the model identifies optimal planting schemes, demonstrating significant improvements in agricultural economic benefits and environmental sustainability.

The results show that the total profits from crop planting in each year are as follows: 6.53 million yuan in 2024, 6.62 million yuan in 2025, 6.58 million yuan in 2026, 6.74 million yuan in 2027, 6.66 million yuan in 2028, 6.57 million yuan in 2029, and 6.64 million yuan in 2030. This indicates that scientific planting strategies and efficient resource allocation can significantly enhance economic returns for farmers. The K-means++ cluster analysis method was applied to classify crops based on economic indicators, further enhancing the model's practicality and reliability. The significant amount of work involved in data collection, model development, and validation underscores the practical value of our approach. The model is feasible and highly beneficial for farmers, providing a systematic and data-driven method for optimal planting decisions.

Future research could focus on incorporating additional factors, such as soil health and pest management, to further refine the model. Extending the model to a larger geographical area and a wider variety of crops would help validate its generalizability and scalability.

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