Research on the Optimal Planting Strategy of Crops Based on Nested Genetic Algorithm

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Abstract. The development of organic farming tailored to the actual conditions of rural areas holds significant practical importance for sustainable rural development. This paper delves into the optimal crop planting strategies under various scenarios, including different sales methods, crop functional interrelationships and uncertainties related to production and costs, market and revenue. Initially, a multi-year total profit optimization model is constructed and solved using a nested genetic algorithm. Subsequently, the Spearman correlation coefficient was used to classify replacement crops and complementary crops to explore the influence of crop functional interrelationships on planting plan and yield. Finally, synthetic aperture radar (SAR) monitoring data is incorporated to assess fluctuations in crop yield per unit area, and the Monte Carlo method is employed to simulate uncertain parameters. Statistical metrics of preselected schemes are analyzed using the TOPSIS method, with the optimal planting strategy ultimately derived by integrating growers' risk preferences.

Keywords: Crop planting, Nested genetic algorithm, Monte Carlo simulation, TOPSIS, Spearman correlation coefficient.

1. Introduction

Under the background of the rural revitalization strategy, rationally planning the planting strategies of crops and enhancing the economic benefits of agriculture have become important ways to achieve sustainable rural development [1]. In recent years, scholars at home and abroad have carried out extensive explorations on issues such as intelligent algorithms, multi-objective optimization and uncertainty management, providing diverse theoretical frameworks and practical solutions for modern agricultural decision-making. Meanwhile, the rapid development of radar remote sensing technology (such as Synthetic Aperture Radar) has provided new technical means for agricultural monitoring. Its all-weather and high-resolution characteristics can achieve dynamic monitoring of key parameters such as crop growth and soil moisture, providing data support for the optimization of planting strategies.

Joel Kostensalo et al. modeled the cumulative effect of crop rotation diversity on soil carbon sinks revealed by dynamically tracking historical cropping sequences [2]. Marcel van Asseldonk et al. verify the robustness of the policy mix under uncertainty by introducing stochastic scenario simulations (e.g., production fluctuations due to climate change) [3]. Aiming at the quantification problem of crop rotation benefits, Salassi et al. innovatively adopted the network flow model to describe the crop alternations relationship, providing a new idea for multi-objective optimization [4]. However, none of the above-mentioned studies have fully integrated policy incentives and uncertain factors. Although Boyabatli et al. introduced the variable of market price fluctuations under the framework of stochastic programming [5], they ignored the impact of costs on long-term returns. Benini et al. proposed a novel decision-making framework that integrates arc flow integer linear programming and column generation meta-heuristic algorithms, providing a more scientific solution for planting [6]. However, none of them integrated the dynamic impact of real-time environmental data (such as soil moisture monitored by radar and extreme weather) on decision-making. Furthermore, the existing studies have insufficient consideration of the heterogeneity of growers' risk preferences and lack a collaborative analysis of the relationship between crop functions and market fluctuations.

To comprehensively consider crop rotation and sustainable land development, as well as the substitutability, complementarity of crops and the uncertainty of parameters under fluctuations in market supply and demand, this work, based on the historical statistical data of crop planting profits in a certain rural area [7], constructed a profit optimization model for long-term returns over many years. For the data with high space complexity, the nested genetic algorithm was applied to improve the solution efficiency. Monte Carlo was used to simulate the profit fluctuations under uncertain conditions, and several optimized planting schemes for crops in the next 7 years considering risk factors were obtained. The TOPSIS method was used for comprehensive evaluation to obtain the long-term optimal planting scheme of crops.

2. The optimization model for the best planting plan of crops

2.1. Establishment of the optimal function

This article focuses on the period from 2024 to 2030. In order to quantify the economic benefits of agriculture more directly, this paper selects profit as the measurement indicator. Leguminous crops in each plot of land should be planted at least once within three years and are subject to restrictions such as no continuous cropping. This means that the annual profits over several years will influence each other and the planting plan for each year cannot be optimized in isolation. When the total profit of these seven years is the largest, the corresponding planting plan is the best.

An analysis of different crops reveals that the crops grown in the greenhouses in the second quarter are harvested the following year. Their planting costs are included in the total cost of the current year, while the sales revenue belongs to the next year. The crops in the remaining land are all sown and harvested in the current year.

Let seasonally related decision variables $x_{ij}(t)$. denote the area of crops j planted in the plot i and sold in the year t, $x_{ij}'(t)$ denote the area of crops j planted in the year t and sold in the following year. Suppose there are m plots of land. Let y_{ij} denote the yield per mu of the crop j planted in the plot i. Then the total output of the crop j in the year $Q_{ij}(t)$ is:

$$Q_j(t) = \sum_{i=1}^{m} x_{ij}(t) \cdot y_{ij} + \sum_{i=1}^{m} x_{ij}'(t-1) \cdot y_{ij} \tag{1}$$

Let c_{ij} denote the unit planting cost of crop j planted in plot i, then the total planting cost of crop j in year t can be describe as:

$$C_j(t) = \sum_{i=1}^{m} x_{ij}(t) c_{ij} + \sum_{i=1}^{m} x_{ij}'(t) c_{ij} \tag{2}$$

Let e_j denote the expected annual sales volume of the crop j, p_j denote the normal selling unit price of the crop j, η is the ratio of the selling unit price of the unsold part to the normal selling unit price, then the total annual revenue $W_{ij}(t)$ of the crop j in year t is:

$$W_j(t) = \min\left(Q_j(t), e_j\right) \cdot p_j + \max\left(Q_j(t) - e_j, 0\right) \cdot p_j \cdot \eta \tag{3}$$

The profit in the year t is:

$$P(t) = \sum_{j=1}^{n} \left(W_j(t) - C_j(t)\right) \tag{4}$$

Where, $P(t)$ is the sum of the profits for the year 2024 to 2030.

In view of the influence of key factors such as the limitation of land use area, the obstacle of continuous cropping of crops, the rotation of leguminous crops, and the threshold of the minimum planting area of a single crop on the planting plan [8], and looked up areas of knowledge and research advances in the field of crop rotation [9], the following constraints are constructed.

Different crops can be planted in the same plot each season, but the growth space occupied by all crops should not exceed the area s_i:

$$0 \le \sum_{j=1}^{n} x_{ij}(t) \le s_i \tag{5}$$

In addition, it is necessary to take into account that continuous cropping of crops, also known as consecutive cropping, can lead to adverse factors such as the accumulation of harmful pathogenic bacteria, thereby increasing the risk of reduced crop yields. For land where only one-season crop can be grown within a year:

$$x_{ij}(t) \cdot x_{ij}(t-1) = 0 \tag{6}$$

For land that can grow two-season crops within a year:

$$\begin{cases} x_{ij}'(t-1) \cdot x_{ij}(t) = 0 \\ x_{ij}(t) \cdot x_{ij}'(t) = 0 \end{cases} \tag{7}$$

To ensure soil health and crop diversity, leguminous crops should be planted at least once in each plot within a three-year cycle:

$$x_{ij}(t-1) + x_{ij}(t) + x_{ij}(t+1) + x_{ij}'(t-1) + x_{ij}'(t) + x_{ij}'(t+1) \ge s_i \tag{8}$$

Where, j is the number of the leguminous crop.

To ensure the efficiency of field operations and the convenience of management, the minimum planting area for each crop on a single plot is 10% of the plot's total area.

As shown above, the optimized model obtained is as follows:

$$\max P = \sum_{t=1}^{7} P(t) \tag{9}$$

$$s.t. \begin{cases} 0 \le \sum_{j=1}^{m} x_{ij}(t) \le s_{\mathrm{i}} \\ x_{ij}(t) \cdot x_{ij}(t-1) = 0 \\ x_{ij}'(t-1) \cdot x_{ij}(t) = 0 \\ x_{ij}(t) \cdot x_{ij}'(t) = 0 \\ x_{ij}(t-1) + x_{ij}(t) + x_{ij}(t+1) + x_{ij}'(t-1) + x_{ij}'(t) + x_{ij}'(t+1) \ge s_i \\ x_{ij}(t) \ge \alpha s_i \\ x_{ij}'(t) \ge \alpha s_i \end{cases} \tag{10}$$

Where:

$$\begin{cases} P(t) = \sum_{j=1}^{n} \left(W_j(t) - C_j(t) \right) \\ W_j(t) = \min\left(Q_j(t), e_j \right) \cdot p_j + \max\left(Q_j(t) - e_j, 0 \right) \cdot p_j \cdot \eta \\ C_j(t) = \sum_{i=1}^{m} x_{ij}(t) c_{ij} + \sum_{i=1}^{m} x_{ij}'(t) c_{ij} \\ Q_j(t) = \sum_{i=1}^{m} x_{ij}(t) \cdot y_{ij} + \sum_{i=1}^{m} x_{ij}'(t-1) \cdot y_{ij} \end{cases} \tag{11}$$

2.2. Planting strategy solution based on nested genetic algorithm

To address the issue of the long span of the 7-year planting plan, this study adopts the nested genetic algorithm. The first layer of the genetic algorithm takes the planting plan of 2023 as the starting point, evolves the plan for the next seven years, and selects the individuals that meet the constraint conditions. The second layer of genetic algorithm is based on the outstanding individuals screened out in the first layer and further evolves the planting plan from 2027 to 2030. Meanwhile, to ensure the coherence and efficiency of the algorithm, the two sets of algorithms remain consistent in terms of the definition of the fitness function, the screening of elite individuals, and cross-design, thereby achieving an effective planning of the 7-year planting plan. The specific design of the genetic algorithm is as follows:

First is the selection of algorithm parameters. To ensure the efficiency of the algorithm, the population size is set to 40, the crossover probability to 0.7, the first layer of evolution algebra to 100, and the second layer of evolution algebra to 20. Subsequently, the coding method is determined. The corresponding relationship between plots and planted crops is extracted from the existing data. The specific requirements and restrictions of different plot types on crop planting are clarified. The annual planting plan is regarded as an individual's chromosome. In addition, population initialization is required. Due to the high spatial complexity of the planting plans from 2024 to 2030 in the actual selection process of planting plans, rapid positioning is feasible and difficult to solve. To identify a batch of initial individuals that meet the basic constraint conditions, in the first layer of the genetic algorithm, the planting plan of 2023 is adopted as the starting point to ensure that the randomly generated plan first conforms to the specific constraints of crop rotation, land use efficiency and crop planting. On this basis, individuals that meet other constraint conditions are further screened out. In the second layer of the genetic algorithm, the construction of the initial population relies on the excellent individuals screened out in the first layer. This can improve the execution efficiency of the algorithm. Secondly, a fitness function is defined to evaluate the fitness of individuals in the population. Since the greater the benefit of the planting plan, the higher the corresponding fitness, the 7-year total profit of this planting plan is adopted as the fitness function. To select individuals with higher fitness, first sort the individuals according to fitness, and select the individuals ranked in the top 1/8 of fitness to replace those ranked in the bottom 1/8. Subsequently, the individuals are sorted according to the size of their fitness, and those with high fitness are given priority for crossover. Whether to cross or not is determined by the probability of crossing. If crossing occurs, randomly select points to exchange chromosome fragments. Individuals that have not crossed or reached the iteration limit are directly replicated to the new population. To retain outstanding individuals, an elite protection strategy is adopted. If the fitness of the new individual is lower than that of the parent generation, re-select the crossover points for iteration until the fitness improves or the iteration limit is reached, and then stop trying.

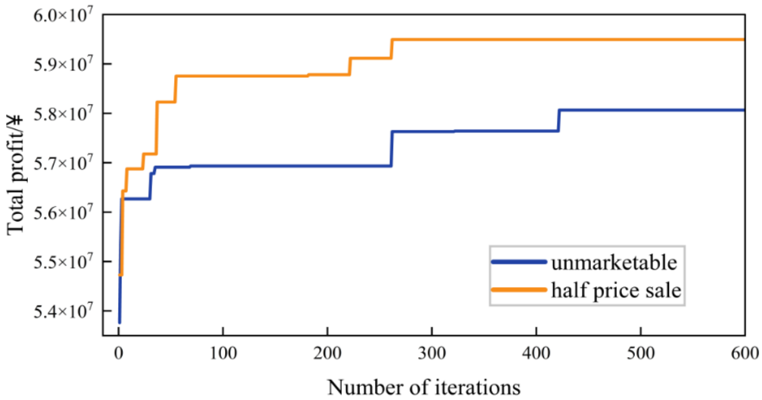

Figure 1. Nested Genetic Algorithms to Solve for Profit Results

The optimal planting strategy is given by solving the model through the steps of the nested genetic algorithm mentioned above. This article fully considers the situation where the crop yield exceeds the expected sales volume and can be divided into two sales strategies: one is that the excess part remains unsold, and the other is that the excess part is sold at half price. It can be seen from Figure 1 that if the excess part of the crops is treated as unsold (indicated by the blue curve), then after about 450 iterations through the nested genetic algorithm, the total profit over 7 years can reach 58.083 million yuan. If the excess crops are treated at 50% of the sales price in 2023 (indicated by the orange curve), after 250 iterations of the nested genetic algorithm, the total profit over 7 years can reach 59.4943 million yuan. When there is an overproduction of crops, the practice of selling the excess part of the crops at a reduced price is far superior to the practice of overstocking and waste. This also reveals a rule: To maximize profits, farmers should increase crop yields. When they find that the crops are about to be overstocked, they should immediately reduce the price for disposal instead of keeping them until they are overstocked and wasted.

3. Substitution-Complementarity Model

In real life, there may be substitutability and complementarity among various crops, and there is also a certain correlation between sales prices, planting costs and expected sales volumes. This paper incorporates these relevant factors into the above-mentioned optimization model to make the results more in line with the actual situation.

3.1. Crop Correlation Analysis Based on Spearman's Rank Coefficient

Generally, alternative crops refer to crop types that are in competition in terms of market demand and resource utilization. Their product functions or consumption scenarios are highly overlapping, resulting in a negative correlation in market sales, such as the substitution competition between corn and other crops (such as soybeans) in the feed sector [10] and the resource competition among intercropped crops [11]. Complementary crops, on the other hand, achieve efficient resource utilization or ecological benefits through co-cultivation. For instance, intercropping legumes and cereals can enhance soil nitrogen fixation, or the combination of fruits and vegetables can meet diverse consumer demands. In terms of yield and market synergy, they usually show a positive correlation.

Based on the seven-year optimal planting scheme derived from the model for profit maximization, this study analyzes crop sales and yields using Spearman’s rank correlation coefficient ($\alpha = 0.05$). Crops with strong negative correlations are considered substitutes, whereas those with strong positive correlations are deemed complements.

3.2. Improvement of the Optimal Crop Planting Plan Model

3.2.1 Update of the objective function

(1) Profit Disturbance Factors of Substitute Crops

If there is an alternative relationship between crops, they will have a competitive relationship in the market. An increase in the planting quantity of crop j will lead to a decrease in the expected sales volume of crop i, thereby reducing the profit of crop i.

$$e_i'(t) = e_i(t) - \sum t_{ij} \cdot Q_j(t), Z_{\text{sub},i}(t) = -\sum t_{ij} \cdot Q_j(t) \cdot p_i(t) \tag{12}$$

Where, $Z_{\text{sub},i}$ denotes the profit decrease caused by the substitute crop i, t_{ij} is the competitive coefficient of crop j with respect to crop i, $p_i(t)$ is the selling unit price of crop i in year t.

(2) Factors Affecting Profit of Complementary Crops

If crops have a complementary relationship, they will mutually promote each other during market sales. An increase in the planting quantity of crop j will lead to an increase in the expected sales volume of crop i.

$$e_i'(t) = e_i(t) + \sum l_{ij} \cdot Q_j(t), Z_{\text{com},i}(t) = \sum l_{ij} \cdot Q_j(t) \cdot p_i(t) \tag{13}$$

Where, $Z_{\mathrm{com},i}(t)$ denotes the increase in profit cause by crop i, l_{ij} denotes the promotion coefficient of crop j for crop i.

(3) Objective function

The objective function obtained from the above model is updated on the final objective function:

$$\max P=\sum_{t=1}^{7}\left(W(t)-C(t)+\left(\sum_{i=1}^{n}Z_{\mathrm{com},i}+\sum_{i=1}^{n}Z_{\mathrm{sub},i}\right)/2\right) \tag{14}$$

3.2.2 New constraints

(1) Increased proportion of area under complementary crops

When the crop k and the crop n are complementary to each other, in order to increase profitability, the ratio between them should be within a certain range and the sum of their acreage over all acreage should be a certain percentage:

$$\begin{cases}\tau_{ij_1}\geq\sum_{i=1}^{m}x_{ik}/\sum_{i=1}^{m}x_{in}\geq\tau_{ij_2}\\ \left(\sum_{i=1}^{m}x_{ik}+\sum_{i=1}^{m}x_{in}\right)/\sum_{i=1}^{m}s_i\geq\omega_{ij}\\ \sum_{i=1}^{m}x_{ik}>\sum_{i=1}^{m}x_{in}\end{cases} \tag{15}$$

(2) Reduced proportion of area under alternative crops

When the crop k and the crop n are substitutes for each other, in order to avoid excessive competition, the ratio between them should be in a range where the sum of their planted areas over all areas should be less than a certain percentage:

$$\begin{cases}\varphi_{ij_1}\geq\sum_{i=1}^{m}x_{ik}/\sum_{i=1}^{m}x_{in}\geq\varphi_{ij_2}\\ \left(\sum_{i=1}^{m}x_{ik}+\sum_{i=1}^{m}x_{in}\right)/\sum_{i=1}^{m}s_i\leq\xi_{ij}\\ \sum_{i=1}^{m}x_{ik}>\sum_{i=1}^{m}x_{in}\end{cases} \tag{16}$$

(3) Constraints between sales volume, sales price and growing costs

There is also a correlation between expected sales volume and sales price and planting costs. An increase in planting costs often leads to an increase in sales price to maintain profitability, in which case cost and price show a positive correlation [12]. And according to the elasticity of demand, it can be seen that there is usually a negative correlation between the sales price and the expected sales volume, when the sales price increases, consumers may reduce the purchase volume expected sales volume decreases, and vice versa. Tian Jing and Lv Ping pointed out in their study that the relationship between sales price p and expected sales volume e can be expressed by linear regression [13]:

$$\begin{cases}p_i(t)=\rho\cdot\left(\sum_{j=1}^{m}c_{ij}(t)/\sum_{j=1}^{m}\delta\left(c_{ij}(t)\right)\right)\\ e_i(t)=b-a\cdot p_i(t)\end{cases} \tag{17}$$

where $\delta(c_{ij}(t))$ is the step function and ρ, a, b are the relevant constants:

$$\delta\left(c_{ij}(t)\right)=\begin{cases}1, c_{ij}\neq 0\\ 0, c_{ij}=0\end{cases} \tag{18}$$

3.2.3 Numerical solution of the optimal solution

The annual profit of all crops, profit of complementary crops and profit of replacement crops in different years without considering and with considering the crop functional relationship is obtained by solving using the above algorithm as follows Table.1:

Table.1. Comparison of profits considering complementary and replacement crops or not

Year	2024	2025	2026	2027	2028	2029	2030
Total Annual Profit	784.38	782.18	770.53	789.19	725.63	828.35	795.02
Total Annual Profit*	777.17	781.42	759.79	778.21	717.32	818.53	788.48
Complementary Crop Profit	653.40	640.78	650.39	658.84	597.04	712.92	674.88
Complementary Crop Profit*	645.96	639.77	639.58	647.68	588.54	702.55	668.27
Replacement Crop Profit	387.95	417.26	374.54	383.22	359.01	407.68	392.72
Replacement Crop Profit*	397.73	431.70	379.57	390.16	365.36	417.52	401.60
Profit values with * are the result of solving without considering the crop function relationship.							

From the results of the calculations, it can be seen that in agricultural cultivation, the total annual profit from crops can be further increased if the relationship between crop sales and changes in selling prices and planting costs is fully taken into account, and crop functional relationships are taken into account in crop cultivation, so as to increase the production of complementary crops and reduce the production of replacement crops.

4. Uncertainty-Potential Risk Model

4.1. Acreage fluctuations based on synthetic aperture radar detection data

Synthetic aperture radar (SAR) technology has the advantage of 24-hour all-weather monitoring, along with the development trend of multi-frequency and multi-polarization SAR technology is also becoming more and more common in agriculture, the application of synthetic aperture radar (SAR) in the monitoring of crop growth has become more and more popular, which can detect real-time soil moisture content, extreme weather, or early signs of pests and diseases [14], assisting in dynamic adjustments of crop planting programs.

y_{ij} denotes the acre yield of the crop j planted in the land i. The backscattered cross-sectional area of the land i in the SAR imaging species is σ_i, and its true area is s_i, then there is a scaling factor $\varsigma_i = \frac{s_i}{\sigma_i}$. Due to the SAR movement, antenna caliber and other factors will lead to insufficient detection accuracy and imaging fuzzy and other problems, remember the detection value and the true value of the existence of coefficients. Let $w_{i,SAR}$ denote the water content per unit area of the land i monitored by the SAR image, then its true water content is:

$$w_i = \varsigma_i \cdot w_{i,\mathrm{SAR}} \cdot \iota \tag{19}$$

Let the most suitable water content for planting the crop j be w_j^{opt}, the land water content threshold for determining whether the land j is drought or not be $w_{threshol}$, and the drought tolerance coefficient for the crop j be χ_j Then:

$$y_{ij} = y_{ij}^{\max} \cdot \left[1 - k_j \left(\frac{w_i - w_j^{opt}}{w_j^{opt}}\right)\right] \cdot max\left(0, 1 - \frac{w_i}{w_{threshold}}\right) \cdot \chi_j \tag{20}$$

Ultimately, it can be seen that uncertainties such as weather and moisture content can lead to fluctuations in crop yields.

4.2. Modeling Uncertainty in Normal Distributions

Herrnstein and Murray, in their book The Bell Curve, have put forward a key statistical principle: in numerous natural and social phenomena, when a variable is influenced by a large number of independent factors, its observations tend to follow a normal distribution [15]. In the context of an agricultural economy, key variables such as expected crop sales, acreage, cost of cultivation, and selling price are inevitably affected by a combination of factors and thus exhibit a certain degree of volatility. In this study, the volatility of these variables is assumed to be normally distributed in order to more accurately model real-world uncertainty.

The volatility of the acre yield of the crop j is γ_j the volatility of the cultivation cost of the crop j is θ_j and the volatility of the cultivation cost of the crop j is λ_j, based on the 3σ principle that the range of volatility is distributed with a normal distribution. The distribution of specific parameters is shown in Table.2:

Table.2. Uncertainty parameters and their distribution

Uncertainty Parameters	Crop Type	Parameter distribution
Expected Sales Wheat	Corn	$\beta_6, \beta_7 \sim N(7.5\%, (0.83\%)^2)$
	Other Crops	$\beta_j \sim N(0, (1.7\%)^2)$
Acreage	All Crops	$\gamma_j \sim N(0, (3.3\%)^2)$
Growing Costs	All Crops	$\theta_j \sim N(5\%, (0.16\%)^2)$
Selling Price	Grains	$\lambda_j \sim N(0, (0.03\%)^2)$
	Vegetables	$\lambda_j \sim N(5\%, (0.16\%)^2)$
	Edible Mushrooms	$\lambda_j \sim N(-3\%, (0.67\%)^2)$
	Sheep Belly Mushrooms	$\lambda_j \sim N(-5\%, (0.16\%)^2)$

4.3. Monte Carlo-based feasible solution

4.3.1 Numerical solution of the optimal solution

Normally, Monte Carlo is in a converged state when the statistical parameters remain stable after Monte Carlo simulation [16]. As shown in Figure 2, when the number of simulations is greater than or equal to 40 times, the mean and variance of the fluctuations of expected yield, mu yield, planting cost and selling price are all stabilized, which indicates that the number of simulations meets the requirements and can more comprehensively cover the changes of parameters.

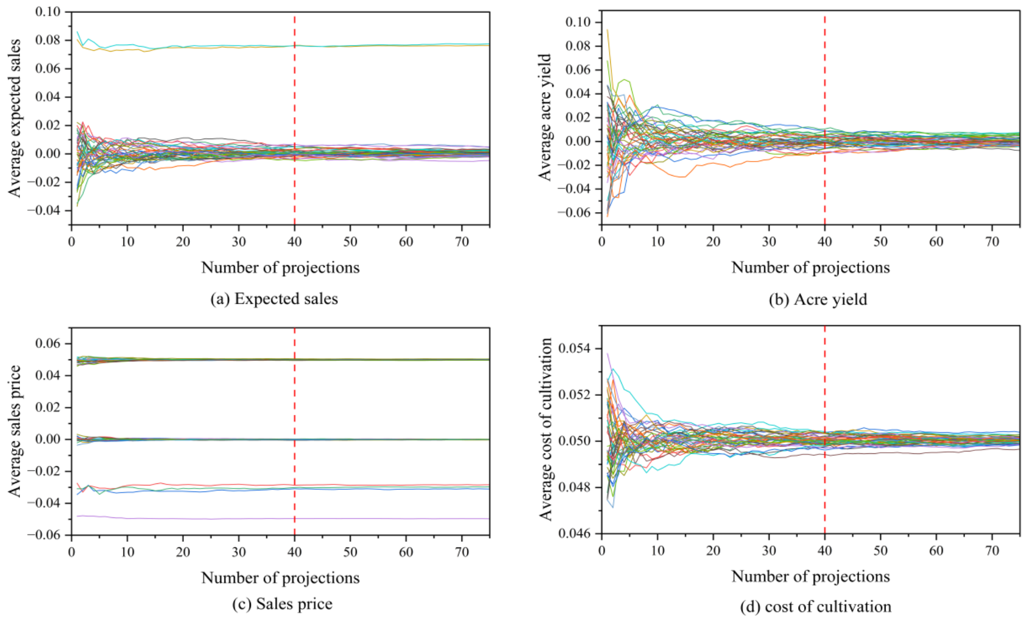

Figure 2. Relationship between parameter means and number of predictions under Monte Carlo simulation

All the parameters obtained from the i-th simulation are brought into the above model, and the total profit in seven years is Π_i. Remember $\Pi_{max} = \max(\Pi_i)$. From the result, we can see that in the range of fluctuation of all four factors there are: $\frac{\Pi_i}{\Pi_{max}} \in [0.93,1]$.

From $\chi_i \in [0.93,1]$, it is clear that the range of variation of the maximum value of the seven-year total profit is not very large within the fluctuation range. It is not possible to use only the maximum value as a criterion for evaluating the merit of the scheme, and the deviation of the scheme profit within a small range of variation of χ_i is small (e.g., the scheme returns corresponding to $\chi_i = 0.93$ versus χ_i=0.94). In order to rationally determine the optimal scheme and cover the key risk-return balance points while reducing the computational burden of parameter space enumeration, this paper adopts the principle of equidistant sampling and takes the profit to be $\Pi_p = 0.93\Pi_{max}$, $0.95\Pi_{max}$,$0.97\Pi_{max}$, Π_{max}, respectively. The corresponding scenarios are denoted as Program I, Program II, Program III, and Program IV, respectively.

4.3.2 Optimal implant program selection

The simulation of the 40 groups of parameters into the four programs to find the maximum value, mean value, extreme deviation and standard deviation of these four programs, and will be used as the basis for the evaluation of planting programs. The higher the maximum value and the mean value, the better the program's return; the smaller the extreme deviation and the standard deviation, the better the stability of the program, the less likely to be affected by the fluctuations of external factors. According to the different degrees of acceptance of risk by farmers, they can be divided into: risk-preferring farmers, risk-averse farmers and risk-neutral farmers.

(1) Risk-averse farmers: they are willing to accept higher risks in order to pursue higher profits. For this type of farmers, the program with high maximum and mean indicators can be chosen.

(2) Risk averse farmers: less willing to accept risk and prefer stable, low-risk agricultural programs or technologies, even if this means lower profits. For this type of farmers, choose programs with small indicators of both standard deviation and extreme deviation.

(3) Risk-neutral farmers: have an average level of acceptance of risk, weighing risk and return in their decision-making, and do not have a particular tendency to favor either high- or low-risk options. For this type of farmers, the four types of indicators need to be synthesized. The following is the process of selecting a program for risk-neutral farmers based on TOPSIS:

Selecting a program with a larger mean and maximum implies higher economic returns, and these two statistics are very large indicators; while a program with a smaller extreme deviation and variance implies the ability to maintain a more stable income in the face of uncertainties, such as market fluctuations and natural disasters, thus reducing business risks, and it is a very small indicator. TOPSIS is a widely used multi-criteria decision analysis method, which ranks the advantages and disadvantages by comparing the distances of the programs from the ideal optimal solution and the worst solution. Very small indicators need to be transformed into very large indicators when performing TOPSIS evaluation: $x' = \frac{1}{x}$. The results of the normalization are shown in Table. 3:

Table.3. Positive statistical indicators for the four programmes

Program	Maximum(￥)	Mean(￥)	Extreme Difference(￥)	Standard Deviation	Polar deviation of normalization ($\times 10^{-6}$)	Normalized standard deviation($\times 10^{-6}$)
Program 1	47076046	46696492	669423.7	166504.7	1.49382	6.00584
Program 2	47962254	47553182	765835.5	182431.1	1.30576	5.48152
Program 3	48107875	47719210	707329.1	185288.3	1.41377	5.397
Program 4	48859982	48489357	808058.7	206384.1	1.23753	4.84534

The proximity between the various programs and the optimal value obtained after the calculation using TOPSIS method is shown in Table. 4 below:

Table.4. Proximity between the four alternatives and the optimal value

	Program 1	Program 2	Program 3	Program 4
R_i	0.4589	0.3498	0.5623	0.5411
Normalized standard deviation	0.2400	0.1830	0.2941	0.2830

As can be seen from Table 4, Program 3 has the highest normalized score, indicating optimal performance, and its specific scenario is the best scenario considering the uncertainty and potential risks.

5. Conclusions

This paper uses nested genetic algorithm to solve the multi-year profit optimization model of crop cultivation, and the conclusions are as follows:

(1) The solution method can efficiently give the planting plan that maximizes the total profit of the crop in 7 years, and effectively reduces the risk of converging to the local optimal solution. In order to maximize crop profits, farmers should increase crop yields, and when they find that the crops are about to become stagnant, they should immediately reduce the price instead of maintaining the original price until stagnation occurs.

(2) In agricultural cultivation, if crop cultivation increases complementary crops and reduces alternative crops, it will further increase the total annual profit, thus farmers need to take crop functional relationships into full consideration during crop cultivation to plant rationally.

(3) The model is assisted by SAR imaging to determine the fluctuation range of the crop's mu yield, taking into account the expected sales volume of the crop, mu yield, planting costs, and the volatility of the sales price, which can be used to formulate the optimal crop planting program suitable for different farmers in terms of their acceptance of risk.

(4) In the future, the practicality of the model and algorithm can be further improved from the perspectives of reducing the time complexity of the nested algorithm and the non-conventionalization of the potential risk perturbation coefficient.

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