

Optimal Planting Strategy of Crops Based on Particle Swarm Optimization Algorithm

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Abstract: Food security is the top priority related to the national economy and people's livelihood. In the context of the shortage of cultivated land resources, rational planning of cultivated land resources planting is an important measure to improve the utilization rate of cultivated land. This study focuses on the use of improved particle swarm optimization to improve cultivated land use efficiency. In order to solve the shortcomings of the traditional particle swarm optimization in dealing with cultivated land use problems, such as slow convergence speed and easy to fall into local optimum, improved strategies such as adaptive inertia weighting and variation operation were introduced. By constructing an optimization model with cultivated land output benefit and resource utilization as the objective function, the improved algorithm is applied to the actual cultivated land use scenario for simulation experiments. Experimental results show that the improved algorithm can quickly converge to the optimal solution, significantly improve the rationality of spatial allocation and utilization efficiency of cultivated land, provide an effective technical means for the efficient management and rational planning of cultivated land resources, and have important theoretical and practical significance for promoting the sustainable development of agriculture.

Keywords: Mixed Integer Programming, Particle Swarm Optimization Algorithm, Pearson Correlation Coefficient, Linear Regression.

1. Introduction

Accurate prediction of crop planting strategies is of great significance to ensure food security and protect the ecological environment. The optimization of crop planting location will directly affect the utilization efficiency of land resources, and is of great significance for improving planting efficiency and reducing costs. Traditional forecasting methods are based on linear regression, such as time series method and analysis method, although there are some improvements in optimizing and simplifying paths, but there are still some shortcomings. For example, Lin Zian [1] analyzed the predictability of the time series method, but the accuracy of the method depends largely on the quality and completeness of the data, and the prediction accuracy is still affected by many factors. Chunjiang Zhu et al. [2] based on linear programming can take into account a variety of constraints to find a better solution, but to a large extent ignore the nonlinear relationship, and there are still deficiencies for market changes in real life. Zhang et al. [3] improved the performance of the particle swarm optimization and proposed a hybrid particle swarm optimization that integrates the advantages of other algorithms. Although this method is optimized for global search, it helps to avoid falling into a local optimal solution. However, there are still limitations such as complex parameter settings and applicable scenario limitations. Therefore, by improving the traditional particle swarm optimization algorithm of Guohao Zhang et al. [4] and combining other ideas such as penalty function, it has played a certain role in optimizing the optimal planting position of crops. This paper first introduces the importance of crop planting strategy prediction and its implications for food security and environmental protection. Then, the main prediction methods used in existing research, including linear regression model, time series method, analytical method, and

hybrid particle swarm optimization method, are reviewed, and the advantages and limitations of these methods are pointed out. Then, the main problems faced by the current crop planting strategy prediction are summarized, including data dependence, ignoring nonlinear relationships, complex parameter settings, and limited application scenarios. Finally, the need to develop new forecasting methods or improve existing methods to improve the accuracy and adaptability of crop planting strategy forecasting is emphasized.

2. The Basic Functions of Particle Swarm Algorithm

2.1. The structure of particle swarm algorithm

Particle Swarm Optimization (PSO) is a heuristic algorithm inspired by swarm intelligence [5], mimicking the cooperative behavior of groups like birds or fish. Each solution, termed a "particle," navigates the solution space, dynamically adjusting its position and velocity based on individual and group experiences. The process involves initialization, fitness evaluation, updating individual and global best values, iterative updates, and checking termination conditions. This is shown in the Figure.1. Particles are randomly generated with initial positions and velocities, their fitness values calculated to assess quality. The current fitness is compared against historical and global bests, updating if better. Subsequently, particle speeds and positions are modified using specific formulas. Finally, termination criteria such as maximum iterations or fitness thresholds are checked to decide whether to output results or continue iterating.

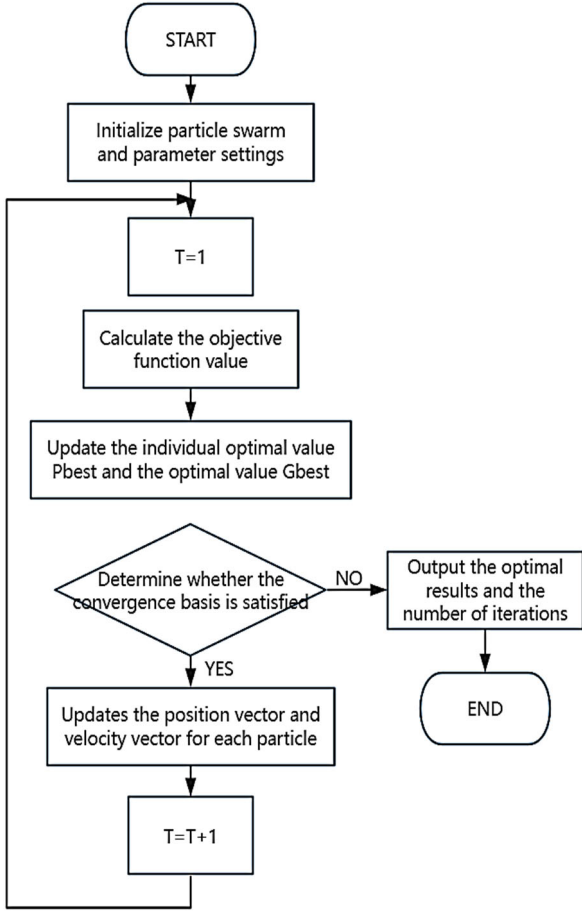


Figure 1. The general flow of particle swarm optimization

2.2. Application of particle swarm algorithm

Particle Swarm Optimization (PSO) has a wide range of applications, including function optimization to solve complex mathematical function problems such as multimodal and nonlinear functions, feature selection and classifiers designed for image processing and data mining in pattern classification, and economic scheduling, state estimation and stability analysis in power system optimization to find the optimal generator output power distribution scheme to maximize economic benefits.

3. Results

3.1. Prediction and change trend of particle swarm optimization for crop sales when constrained

Firstly, check that there are no missing values and outliers in the attachment data, and then visualize the data after integration, and find that the crops that can be planted in various types of land are different under the planting season, so first expand the land number from 1~54 to 1-82, and define and distinguish according to the range requirements, and then establish an integer programming model, which is solved by particle swarm optimization (PSO). The process and results of the planting planning model are as follows:

3.1.1. Objective Functions:

The objective function is established, and the goal is to find the maximum value of the total return in 7 years, and then obtain the optimal planting strategy in 7 years.

$$M = \sum_{j=1}^7 \sum_{i=1}^{82} P_{ij} L_i \mu_{ij} \quad (1)$$

$$T = \sum_{j=1}^7 \sum_{i=1}^{82} S_{ij} C_{ij} \quad (2)$$

$$U = \sum_{j=1}^7 \sum_{i=1}^{82} S_{ij} P_{ij} \quad (3)$$

$$\psi = \sum_{j=1}^7 \sum_{i=1}^{82} S_{ij} \quad (4)$$

$$\eta = \sum_{j=1}^7 \sum_{i=1}^{82} L_i \mu_{ij} \quad (5)$$

$$I_1 = \begin{cases} M - T, & \eta < \psi \\ U - T, & \eta \geq \psi \end{cases} \quad (6)$$

where I_1 represents the profit in the case of waste of unsalable part, P_{ij} represents the sales price of the $Y_{(i,j)}$ crop per mu, L_i represents the planting area of the i th plot, μ_{ij} represents the yield per mu of the $Y_{(i,j)}$ crop, S_{ij} represents the normal sales volume of the $Y_{(i,j)}$ crop in 2023, and C_{ij} represents the planting cost of the $Y_{(i,j)}$ crop.

M : Represents the total planting income of all crops over 7 years when the crop yield is less than or equal to the expected sales volume.

T : Represents the total planting cost of all crops over 7 years.

U : Represents the income obtained from the sales of all crops over 7 years when the crop yield is greater than the expected sales volume.

ψ : Represents the actual production of all crops over 7 years.

η : Represents the total expected sales volume of all crops over 7 years.

The objective function for profit maximization can be expressed as the difference between total revenue and total cost. The total revenue is the sum of the income when the crop yield is less than or equal to the expected sales volume and the income when the crop yield is greater than the expected sales volume. The total cost is the total planting cost.

$$I_2 = \begin{cases} M - T, & \eta < \psi \\ U - T + 0.5 \times \sum_{j=1}^7 \sum_{i=1}^{82} P_{ij} (L_i \mu_{ij} - S_{ij}), & \eta \geq \psi \end{cases} \quad (7)$$

where I_2 represents the profit in the case of the sale of the unsalable part at half discount.

3.1.2. Constraints

The constraints of the function solution are set according to the problem conditions, and the constraints with weak binding force are eliminated, and then the data are calculated and processed by the particle swarm algorithm. Specifically, it is manifested as the constraint problem of particle swarm optimization on the prediction problem and change trend of crop sales.

Flat and dry land, terraced fields, hillside land

$$\begin{cases} Y_{(i,j)} \neq Y_{(i,j+1)}, 1 \leq i \leq 26, 1 \leq j \leq 7 \\ \forall j \in [1,5], i \in [1,26], \exists k \in [j, j+2], \text{ s.t. } Y_{(i,k)} = [17,19] \end{cases} \quad (8)$$

Water the ground

$$\begin{cases} \text{if } Y_{(i,j)} = 16, Y_{(i+28, j)} \text{ Not taken into account} \\ \forall j \in [1,5], i \in [27, 34], \exists k \in [j, j+2], \text{ s. t. } Y_{(i,k)} = [17,19] \end{cases} \quad (9)$$

Ordinary greenhouses

$$\begin{cases} \text{if } Y_{(i,j)} = 16, Y_{(i+28, j)} \text{ Not taken into account} \\ \forall j \in [1,5], i \in [35, 50] \cup [62,77], \exists k \in [j, j+2], \text{ s. t. } Y_{(i,k)} = [17,19] \end{cases} \quad (10)$$

Smart greenhouse

$$\begin{cases} \forall j \in [1,5], i \in [51,54] \cup [79,82], \exists k \in [j, j+2], \text{ s. t. } Y_{(i,k)} = [17,19] \\ Y_{(i,j)} \neq Y_{(i+28,j)}, i \in [51,54] \\ Y_{(i,j)} \neq Y_{(i-28,j)}, i \in [79,82] \end{cases} \quad (11)$$

Due to the large number of results and graphs of the model, only the planting strategies of flat dry land, terraced land and hillside land in case 1 are used. The example shows the model solving process, and the rest of the diagrams are attached in the appendix. After 200 iterations of the particle swarm algorithm, the maximum profit in 7 years is obtained, and the results are shown in Figure 2 below, and the results of some planting strategies are shown in Table 1.

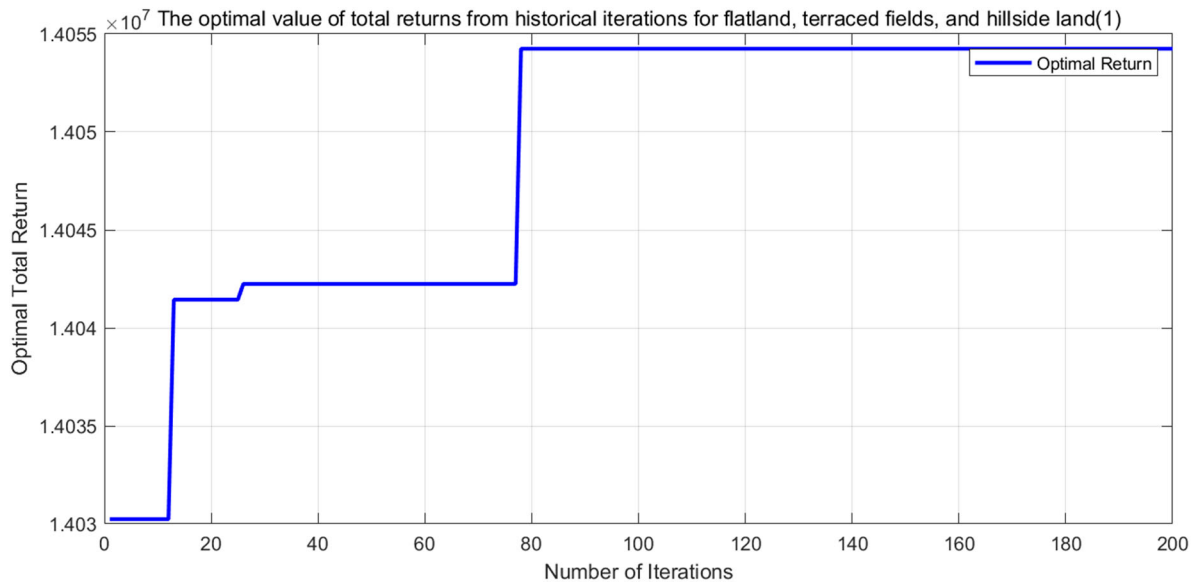


Figure 2. The best historical iteration of total returns for flat and dry lands, terraced fields, and hillside lands

Among them, this part of the objective function (i.e., total profit) is equal to the optimal value: 1.3695×10^7 , which is the total profit of flat and dry land, terraced land and hillside land

in 2024~2030 40,407,466 yuan. Compared to the normal sales profit in 2023 5,940,000 RMB, calculated that the model it designed is feasible.

Table 1. Results of partial planting strategies on flat and dryland, terraced and hillside lands

Plot name	Soybeans	black beans	red beans	mung beans	climbing beans	wheat	Corn	millet	sorghum
A1	0	0	0	0	0	0	0	80	0
A2	0	0	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0	0	0
A4	0	0	0	0	0	0	72	0	0
A5	0	0	0	68	0	0	0	0	0
A6	0	0	0	0	0	0	0	0	0
B1	0	0	0	0	0	0	0	0	0
B2	0	0	0	0	0	0	0	0	0
B3	0	0	0	40	0	0	0	0	0
B4	0	0	0	0	0	0	0	0	28

3.2. The substitutability and complementarity of crops when there are constraints

Analysis of the substitutability and complementarity of crops Through the observation of Annex 1, it can be seen that there are five categories of crops: "grain (legumes)", "grains", "vegetables (legumes)", "vegetables", and "edible fungi". Economic value and eco-friendliness are reflected in many

aspects:

Our improved planting planning model was tested using the Pearson correlation coefficient [6-7] and linear regression pair, and the data of the expected sales volume, planting cost and sales price of crops in 2023 were imported into the SPSS software, and then the multiple linear function model regression [8] was used to analyze the correlation function, and the results are shown in Table 2 and Figure 3 below.

Table 2. Linear regression analysis result table

category	B	standard error	Beta	t	P	VIF	R ²	Adjust R ²	F
Constant	3182.657	853.768	-	3.728	0.001***	-	-	-	-
Plantcost/ (rmb/mu)	0.842	0.279	0.668	3.018	0.006***	1.582	0.318	0.256	F=5.136 P=0.015**
Sales price	-83.869	31.185	-0.596	-2.689	0.013**	1.582	-	-	-

Note: ***, **, and * represent the significance levels of 1%, 5%, and 10%, respectively

In the linear regression analysis, although the overall model was statistically significant (P = 0.001), only the planting cost per mu had a significant positive impact on yield per mu (P = 0.001). Conversely, sales volume and sales price showed no

significant impact (P = 0.814 and P = 0.828, respectively), indicating that these variables have negligible explanatory power for yield changes per mu.

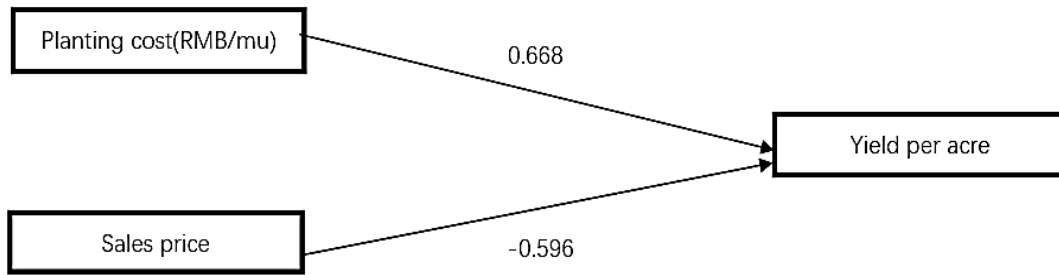


Figure 3. Linear regression model path diagram

Furthermore, the normalized coefficients of sales volume and sales price were -0.038 and -0.033, respectively, indicating negligible impact on yield per mu. Adding these variables does not significantly enhance the model's explanatory or predictive power, allowing their correlation to be ignored in subsequent processing. The adjusted R² value of 0.343 for the linear regression indicates average explanatory power, suggesting that other important factors or nonlinear relationships may be present. Future improvements should analyze additional effects and consider more complex models to enhance accuracy and reliability. In summary, the current analysis shows weak and insignificant impacts from sales volume and sales price, justifying their exclusion in further processing. Other potential influencing factors and methods should be considered to improve the prediction and interpretation of yield changes per mu. Consequently, it concludes that the expected sales volume of crops in 2023, planting costs, and selling prices are not correlated.

3.3. Construction and solution of improved planting planning model

In this paper, it screened the crops that could be planted in the first and second seasons in each category, and screened out some crops with relatively low economic efficiency and no longer planted in the future, so as to construct an improved planting planning model.

Crop Screening:

For crop selection, it used the TOPSIS evaluation model. The TOPSIS method is a multi-criteria decision analysis tool, which evaluates the proximity of each alternative to the ideal solution by constructing an ideal solution and a negative ideal solution, so as to rank the planting priority of crops, and then carry out crop selection.

The steps of Topsis are as follows:

a) We selected four indicators for evaluation: expected sales volume, mu cost, mu yield, crop yield per mu, and sales unit price. Build a data matrix $E = (e_{ij})_{n \times m}$. The e_{ij} is the value of the i th crop on the j th index. The normalized method of vector gauge is used to obtain the normative decision matrix. Normalized decision matrix $B = (b_{ij})_{n \times m}$

$$b_{ij} = \frac{e_{ij}}{\sqrt{\sum_{i=1}^n e_{ij}^2}} \quad (12)$$

b) Construct a weighted gauge matrix $C = (c_{ij})_{n \times m}$,

$$w = [w_1 w_2 \dots w_m] \quad (13)$$

$$c_{ij} = w_j \cdot b_{ij} \quad (14)$$

c) Determine the positive ideal solution C^1 and the negative ideal solution C^0 , and let the j th property value of the positive ideal solution be C_j^1 , and the negative ideal solution is the same.

$$\text{Positive ideal solution: } c_j^1 = f(x) = \begin{cases} \max c_{ij}, & j \in J_1 \\ \min c_{ij}, & j \in J_2 \end{cases} \quad (15)$$

$$\text{negative ideal solution: } c_j^0 = f(x) = \begin{cases} \max c_{ij}, & j \in J_2 \\ \min c_{ij}, & j \in J_1 \end{cases} \quad (16)$$

J_1 is a collection of benefit-based indicators (such as expected sales volume, yield per mu, and sales unit price), and J_2 is a collection of cost-based indicators (such as cost per mu).

d) Calculate the distance of each scheme to the positive and

negative ideal solutions. to the positive ideal solution is s_j^1 and to the negative ideal solution is s_j^0

$$s_j^1 = \sqrt{\sum_{i=1}^m (c_{ij} - c_j^1)^2} \quad (17)$$

$$s_j^0 = \sqrt{\sum_{i=1}^m (c_{ij} - c_j^0)^2} \quad (18)$$

e) Calculate the ranking index value (the comprehensive evaluation index) of each program

$$f_i = \frac{s_j^0}{s_j^0 + s_j^1} \quad (19)$$

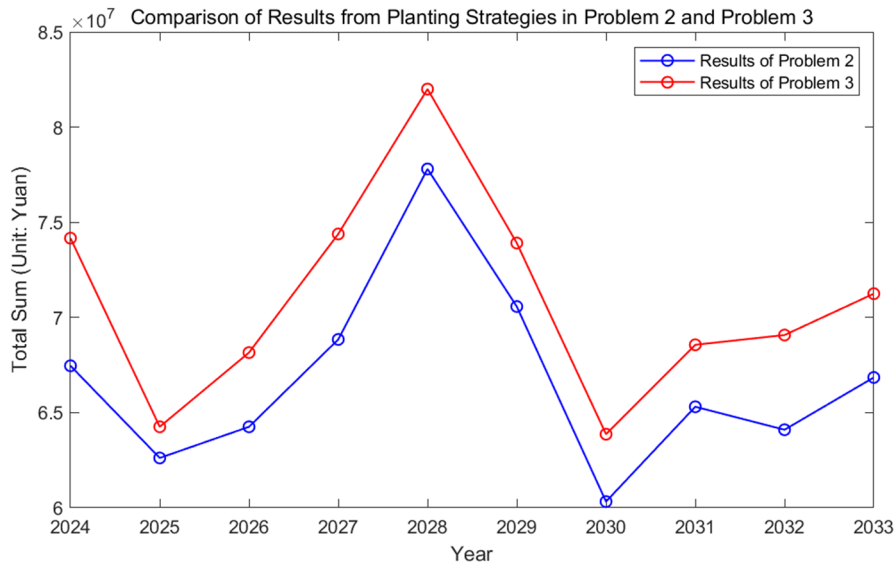


Figure 4. Comparison of economic benefits before and after model optimization

As shown in Figure 4, the average annual total consumption of the improved model according to question 3 is significantly higher than that of the previous model, especially the total consumption in 2028 will reach 8.25×10^7 yuan, and the results of the improved model are better than those of the previous model, which proves that the improved planting planning model has better performance.

4. Conclusions

This paper explores optimizing planting methods in China to enhance cultivated land utilization and address organic farming challenges. A particle swarm optimization-based integer programming model is developed, considering factors like growth characteristics, planting time, cost, yield per mu, and sales price. The model breaks down complex problems into manageable sub-problems for improved efficiency and predicts crop sales trends while examining crop substitutability and complementarity. This addresses issues such as cultivated land shortage and declining planting areas.

The solution simplifies the use of PSO, significantly improving processing speed with large datasets. The model is practical, easy to build, and portable. While the PSO algorithm enables parallel processing for better search efficiency, it may converge prematurely, yielding only local optimal solutions. The model's performance heavily depends on parameter settings like inertia weight, learning factor, and number of iterations; poor parameters can negatively impact

To sum up, the crops it eliminated and their types are: crops in the first quarter: grain (legumes): red beans, mung beans, climbing beans; Grains: sorghum, millet, wheat, barley, sword beans; Vegetables (legumes): kidney beans; Vegetables: spinach, green peppers, cauliflower, cabbage, lettuce, peppers, yellow cabbage crops in the second quarter: vegetables (legumes): sword beans; Vegetables: potatoes, spinach, green peppers, lettuce, baby greens, lettuce, yellow cabbage, celery, carrots; Edible mushrooms: elm mushroom, shiitake mushroom.

Finally, the results of the different models in the two cases are shown as follows:

the results. In order to further improve the algorithm and improve the performance of the algorithm, it suggests that it be mixed with other heuristic algorithms, in addition to increasing the amount of raw data, to improve the accuracy and scientific of the model optimization results. The algorithm can also be used in similar decision allocation problems, and has a wide application prospect.

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