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The Study of Maximizing Profit in Crop Planting Plans Based on Optimization

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Abstract: *The application of digital agricultural technology aims to significantly enhance the efficiency and productivity of agricultural activities through advanced information technology and data analysis methods. However, globally, the growth rate of food production still lags behind the expansion rate of the population, leading to a serious issue: the limited nature of arable land resources. To address this challenge, the rational utilization and management of limited arable land resources have become one of the key strategies for improving the benefits of crop cultivation. In this paper, particle swarm optimization algorithm, Monte Carlo model and neural network model were used to optimize crop planting plan, increase crop planting quantity, planting area and annual planting frequency, reduce production cost, increase crop planting income, and maximize crop planting benefits. The results showed that adjusting crop planting plan had a great impact on crop planting income, and optimizing crop planting plan had a significant effect on improving crop planting income. At the same time, the intelligent optimization algorithm has a good performance in the optimization of crop planting scheme, and the optimization effect of the combined optimization algorithm is also worth looking forward to.*

Keywords: *Particle Swarm Optimization (PSO), Monte Carlo Model, Crop Planting Scheme, Artificial Neural Network Architecture(ANN), Maximize revenue*

1. Introduction

The contradiction between the expanding population size and the increasing shortage of resources has shown a trend of continuous aggravation in various industries around the world, especially in agricultural production. The new agricultural production form, which uses digital information technology for information management of agricultural objects, is a typical application of digital reorganization in the upgrading of traditional agriculture. Digitalization implies that management tasks on-farm and off-farm focus on different sorts of data, using sensors, machines, drones, and satellites to monitor animals, soil, water, plants and humans [1]. The digitalization enables farmers to control their farms remotely and manage agricultural activities in a more effective way [2]. Currently, the growth in agricultural production is not sufficient to keep up with the growing population, which may result in a food shortfall for the world’s inhabitants [3]. Cultivated land resource is an important factor in agricultural production. However, the cultivated land resources are limited in the real world, so it is very important to use the cultivated land reasonably to improve the economic benefits of agricultural products and avoid various uncertain risks.

The term "maximization" refers to a class of problems related to optimization. The optimization method is to conduct a search, evaluate and analyze countless possible solutions, so as to find the best solution to the problem, where the number of searches for the possibility will be detailed is very large, even unimaginable. Linear programming is a problem-solving method that deals with the use of multiple resources and commodities to produce multiple products [4]. Traditional linear programming methods can reduce the "search space" - the number of solutions to be searched. Because any problem has limitations, a large number of solutions are excluded according to the limitations, and the optimal solution is selected from the remaining solutions. This leads again to the problem of having to evaluate all possible solutions - an impossible task [5]. Traditional optimization methods often require processing large

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amounts of data, which is time-consuming and inefficient, and has obvious limitations. To overcome the mentioned problem, introducing new metaheuristic optimization algorithms to deal with the drawbacks of classical techniques has been of great concern [6]. A set of solutions is randomly generated and iteratively updated until the standards are met. In PSO, each potential solution to a given problem is viewed as a particle with a certain velocity flying through the space of the problem just like a flock of birds [7]. Monte Carlo method can truly simulate the actual process of crop planting, and very satisfactory results can be obtained through optimization iteration. ANN is a machine learning prediction model that can predict the expected output when trained with a data-set of inputs and output [8]. The use of intelligent optimization algorithm can provide excellent performance in solving the problem of crop planting optimization, so as to get better results.

This paper aims to explore the influence of different planting schemes on crop yield changes, improve crop planting amount, planting area, planting times in a year and reduce production costs by optimizing crop planting schemes, and increase crop planting income by increasing yield and reducing cost. To this end, three optimization algorithms are used, namely simulated particle swarm optimization algorithm, Monte Carlo model and neural network model. Through the application of these optimization algorithms, we can find out the key factors that affect the crop planting yield, and design the best program of crop planting to maximize the crop planting benefit.

2. Methodology

2.1 Description of the Dataset

The experimental data we use are from the questions of the National Mathematical Modeling Contest for College Students, which can be found at https://www.mcm.edu.cn.The data set includes specific data details of planting plot, serial number, crop number, crop name, crop type, planting area, planting season, plot type, per mu yield, planting cost, unit price of sales, plot area, total production and cost. The data was collected in 2023. These data can be used to construct optimization models and improve crop planting benefits by optimizing crop planting schemes. Crop planting in 2023, relevant statistical data in 2023, existing farmland in the countryside, and crops planted in the countryside constitute a dataset with a large number of samples.

2.2 Data preprocessing

2.2.1 Data integration

Different worksheets provide data about plots, crops, etc., and connect data from different worksheets through common fields such as crop number and plot name. Use the "VLOOKUP" or "MATCH" functions to match the data and ensure that all cells are the same when merged.

2.2.2 Data association

According to the common fields, the data were combined, and the types and areas of the plots and the planting information of crops were analyzed by the fields of "plot name" and "crop number". In Excel, you associate two worksheets with Pivottables for more efficient analysis.

2.2.3 Data aggregation

The information is summarized by calculating the total cost of growing the crop, the total income, and the yield. For each combination of crop and plot type, a summary function such as "SUM" or "AVERAGE" is used to sum, calculate the mean, or perform other aggregation operations to get overall statistics for the 2023 crop. Use Excel Pivottables to group and summarize data by year, quarter, or other dimensions by selecting fields such as crop name, plot type, etc.

2.2.4 Deletion analysis

Missing value detection: Using SPSS's Missing Value Analysis tool, identify which fields are missing and check the pattern of missing values. Outlier detection: Use the tool in SPSS to check whether there are outliers, and the results show that all are valid data.

2.2.5 Irrelevant data processing

SPSSPOR was used for invalid sample analysis, and the judgment criterion was set as the same data was repeated by 50% or more, and no irrelevant data was found.

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2.3 Simulation particle swarm optimization model

In the case that more than a portion is sold at a 50% discount, an objective function is established to maximize the total revenue.

When total production ≤ expected sales: F2= sales price * expected sales - planting area * planting cost

When total production > expected sales volume: F2= selling price * expected sales volume +0.5* Selling price * (total production - expected sales volume) - planting area * planting cost

$$\mathrm{MAXZ} = \sum_{y=1}^{7} \sum_{d=1}^{2} \sum_{a} \left(P_a \min\left(g_{a,d,y}, L_a\right) + 0.5 * P_a \max\left(g_{a,d,y} - L_a, 0\right) - C_a \cdot \sum_b s_{a,b,d,y}\right) \quad (1)$$

Where, y represents the year (2024, and so on), a represents the crop name, b represents the plot name, d represents the planting season, C_a represents the planting cost, P_a represents the selling price of crop a, L_a represents the expected sales volume of crop a, Q_a represents the mu yield of crop a, $g_{a,y} = \sum_{b \in B} s_{a,b,d,y} \cdot Q_a$ represents the total output of the first crop a in the y year, and $s_{a,b,d,y}$ represents the total output of the first crop a in the y year. On plot b or greenhouse, the area where crop a is planted in quarter d.

Constraints:

1) Cropping restriction: For each plot b, the same crop a cannot be planted in two consecutive years or two seasons. A binary variable q is introduced to represent the category of planting, $q = 1$ means planting, $q = 0$ means no planting, and the sum of the value of q in y year and the value of $y + 1$ year is less than or equal to 1.

The constraint formula is as follows:

$$s_{a,b,d,y} \cdot s_{a,b,d,y+1} = 0, \forall a, b, d \in \{1,2\}, y \in \{1, \ldots ,6\} \quad (2)$$

2) Legume crop frequency constraint: Each plot b (or greenhouse) needs to plant a legume crop (grain legume v2 or vegetable legume v4) at least once in three years, where v indicates the crop type.

The constraint formula is as follows:

$$\sum_{y}^{y+2} \sum_{a \in \left\{a \middle| v_a \in \{v_2, v_4\}\right\}} s_{a,b,d,y} \geq A_b, \forall b, d \in \{1,2\}, y \in \{1,2,3,4,5\} \quad (3)$$

3) Crop planting concentration constraint: We set the minimum planting area to 0.1 mu, so the planting area $s_{a,b,d,y}$ must be greater than or equal to 0.1 mu. Here, the minimum planting area threshold and the maximum dispersity index threshold of a single plot can also be selected to determine the area suitability constraint. The concentration constraint method is adopted in this paper.

The constraint formula is as follows:

$$s_{a,b,d,y} \geq 0.1 \cdot f_{a,b,d,y}, \forall a, b, d \in \{1,2\}, y \in \{1, \ldots ,7\} \quad (4)$$

Among them, the $f_{a,b,d,y}$ as binary variables, when $g_{a,y} > 0$, $f_{a,b,d,y} = 1$; Otherwise, $f_{a,b,d,y} = 0$. This paper did not determine the specific planting plots, but simply restricted the minimum planting area of the whole crop.

4) Multiple constraint for planting area 0.1: To ensure that $s_{a,b,d,y}$ is a multiple of 0.1, we can express $s_{a,b,d,y}$ as an integer multiple of 0.1.

The constraint formula is as follows:

$$s_{a,b,d,y} = 0.1 \cdot y_s, y_s \geq 0, \forall a, b, d \in \{1,2\}, y \in \{1, \ldots ,7\} \quad (5)$$

Where y_s is a non-negative integer, indicating that the planting area $s_{a,b,d,y}$ is an integer multiple of 0.1.

2.4 Monte Carlo algorithm model

Crop sales are affected by many factors, such as market demand, supply, and weather conditions. The constraints of the simulated particle swarm algorithm can still be used, so we will not go into details here. Add constraints:

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1) The expected sales volume of wheat L_w and corn L_c in the future has an increasing trend, with an average annual growth rate between 5% and 10%, and the expected sales volume of other crops in the future will change by about ±5% compared with 2023. Where, r_w and r_c represent the annual growth rate of wheat and corn, respectively, and their values range from 5% to 10%. The equation is as follows:

$$L_w(y) = L_w(2023) \cdot (1 + r_w)^y, y \in \{1,2,3,4,5,6,7\} \tag{6}$$

$$L_c(y) = L_c(2023) \cdot (1 + r_c)^y, y \in \{1,2,3,4,5,6,7\} \tag{7}$$

$$L_a(y) = l_a(2023) \cdot (1 + \delta_a) \tag{8}$$

2) The yield per acre varies by ±10% per year due to the climate. Where $\gamma_a \in [-0.05,0.05]$ represents the annual sales volume change of crop a. The per mu yield of crops is often affected by climate and other factors, and there will be a change of ±10% per year.

$$p_a(y) = p_a(2023) \cdot (1 + \gamma_a) \tag{9}$$

3) The price of edible fungi is falling by 1 to 5% per year. The sales price of edible fungi is stable and has declined, about 1% to 5% per year.

$$P_{mu}(y) = P_{mu}(2023) \cdot (1 - r_{mu})^y \tag{10}$$

4) The fluctuation of total income can be constrained to ensure that planting income does not fluctuate too much in extreme circumstances:

$$\mathrm{Var}(Z) \le \sigma_{max} \tag{11}$$

Objective function :Z= expected sales * sales price - planting area * planting cost +(planting area * per mu yield - expected sales) *(selling price *50%- planting cost/per mu yield)

$$\mathrm{MaxE}(Z) - \lambda \cdot \mathrm{Var}(Z) \tag{12}$$

E is for planting expectations. Var is the variance. λ is a risk-averse factor that measures the balance between return and risk, with higher λ indicating a more conservative decision and lower λ indicating a more revenue-biased decision.

2.5 Neural network algorithm model

$$\mathrm{MaxE}(Z) - \lambda \cdot \mathrm{Var}(Z) + Ad \tag{13}$$

$$Ad = \sum_{a,j,k} \left[R_{jk} \cdot \left(s_{aj}^y \cdot s_{ak}^y\right) - T_{jk} \cdot \left(s_{aj}^y \cdot s_{ak}^y\right) + \rho_{jk}\right]_{\downarrow} \tag{14}$$

Add the following parts to the objective function of the Monte Carlo model:

Where, Rjk represents the complementarity coefficient between crop j and crop k. Whether higher yields, quality, or returns are shown when planted in the same or adjacent plots, and if there is a significant improvement, the two crops are highly complementary.

Where, $R_{jk} =$ (total yield from combined cultivation - total yield from separate cultivation)/total yield from separate cultivation.

$R_{jk} > 0$ indicates a complementary effect, and the larger the value, the stronger the complementarity.

$R_{jk} \le 0$ indicates no complementary effect or negative effect.

T_{jk} represents the fungibility coefficient between crops j and k.

$T_{jk} =$ Rate of change in demand of crop k/rate of change in price of crop j.

$T_{jk} > 0$ indicates that j and k are substitutes, and the larger the value, the stronger the substitution.

$T_{jk} < 0$ indicates that j and k may be complementary.

ρ_{jk} represents the correlation coefficient between crops j and k. The correlation coefficient can be solved.

s_{ab}^y represents the area of crop a planted on plot b of year y.

Add further constraints:

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1) Complementary constraints:

$$\left[R_{jk} \cdot \left(s_{aj}^{y} \cdot s_{bk}^{y}\right)\right] \geq \text{Minimum complementary requirements} \tag{15}$$

2) Fungible constraints:

$$\sum_{i} \left[T_{jk} \cdot \left(x_{aj}^{y} \cdot x_{bk}^{y}\right)\right] \leq \text{Maximum fungible limit} \tag{16}$$

Complementarity between crops can enhance the total yield of crops, while intercrop substitutability can put downward pressure on prices. By subtracting, the model tends to choose the crop combination with strong complementarity and weak fungibility. In this way, you can optimize returns while also reducing the risk of market volatility and uncertainty.

3. Results and discussion

3.1 Simulation particle swarm optimization model

In PSO, as in solving optimization problems, where a flock of birds is interpreted as a swarm of particles, each representing a candidate solution, the swarm of particles searches the space in a given dimension and finds the best solution to optimize the problem at hand [9]. The steps of simulating particle swarm optimization are as follows.

Step1) Parameter initialization;

Reduce the randomness of the simulated particle swarm algorithm and perform 51 runs as the final fitness curve.

Step2) Zeroth generation population particle initialization;

Prepare for entering the loop.

$$\text{Pop} = \text{Pop max} \cdot \text{rand} \tag{17}$$

$$V = \text{Vmax} \cdot \text{rand} \tag{18}$$

Step3) Zeroth generation population optimization;

Step4) Renewal.

$$V(V(j) > \text{Vmax}) = \text{Vmax} \tag{19}$$

Considering that if the total output of a certain crop exceeds the corresponding expected sales volume in each season, the excess part will produce sluggish sales, and the excess part will be sold at a discount of 50% of the sales price in 2023, the model solution results are shown in the Figure 1.

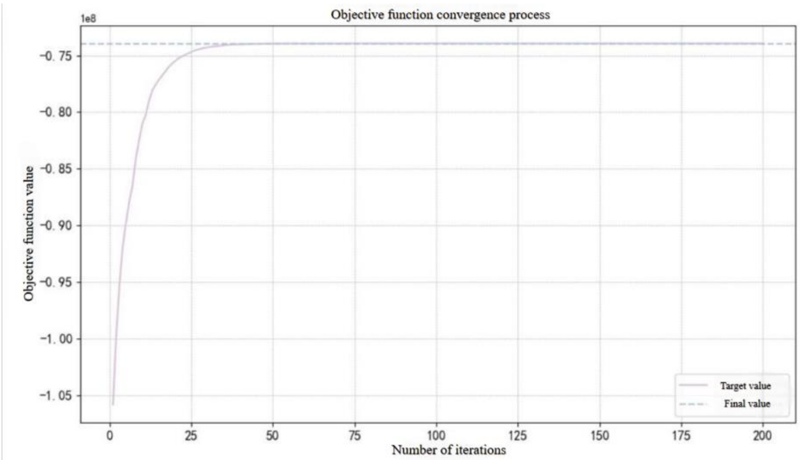

Figure 1. Simulation results of particle swarm optimization

The results are obtained through continuous iteration of the objective function, as shown in the figure below. At the beginning, the value of the objective function changes greatly, but with the gradual increase of the number of iterations, the value of the objective function gradually becomes stable, and remains

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stable after reaching the final target value, indicating that the total income becomes more and the model optimization effect is better.

3.2 Monte Carlo model solving

Monte Carlo algorithm takes probabilistic thinking as the research core, constructs the corresponding probabilistic model through numerical simulation and statistical check, and tests the randomness of the corresponding simulation through random probability [10].

Step1) Randomly extract the values of multiple elements as input;

Step2) Sum the values of all the elements to get the cost value of the whole project;

Step3) Repeat step 1 and step 2, you need to simulate many times and you end up with multiple values;

$$F_N = \frac{1}{N}\sum_{i=1}^{N} f(x_i) \tag{20}$$

Step4) Through statistical analysis of these massive simulation values, the final solution is obtained.

Considering that sluggish sales will occur if the product exceeds the corresponding expected sales in the sales process, the model solution results are shown in the Figure 2.

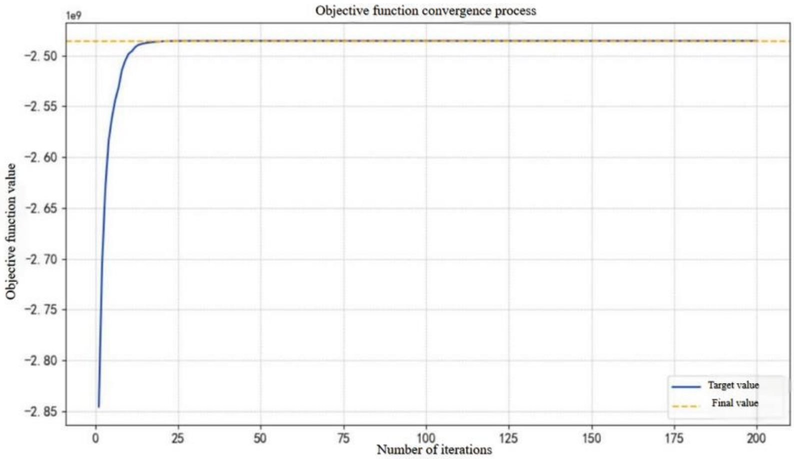

Figure 2. Monte Carlo model solution results

As can be seen from the above analysis, with the increase of the number of iterations, the value of the objective function rapidly increases to the maximum value, and the final target value is slightly lower than that of the simulated particle swarm optimization algorithm, but the number of iterations is less, indicating that the optimization effect is better.

3.3 Neural network model solving

ANN is a well-known soft computing technique that was developed based on the biological mechanism of the human brain[11]. The neural network model contains multiple layers, each of which is composed of multiple neurons. Different layers are connected with each other through neurons, and each connection has a weight. The neural network is constantly learning how to adjust the weight to improve the adaptability of the model.

Neuron composition formula:

$$a = g(\sum_{i=1}^{n} w_i x_i + b) \tag{21}$$

Step1) The architecture of all neural networks is selected and the parameters are initialized.

Step2) Linear + activation function combination to enable data flow in the network;

The sigmoid function: $g(z) = \frac{1}{1+e^{-z}}$

ReLU function: $g(z) = \max(0, z)$

Z—Neuronal input

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Step3) The cross-entropy function is used to complete the costing

Cross entropy function:

$$Cross-entropy=-\frac{1}{n}\sum_{i}^{n}\left(y_i\log(y_i^{\wedge})+(1-y_i)\log(1-y_i^{\wedge})\right) \tag{22}$$

Step4) Training model (including propagation and updating)

Update function:

$$w_{ij}^{(l)}=w_{ij}^{(l)}-\alpha\frac{\partial J}{\partial w_{ij}^{(l)}} \tag{23}$$

Considering that there are certain substitutability and complementarity between crops, the model solution results are as Figure 3.

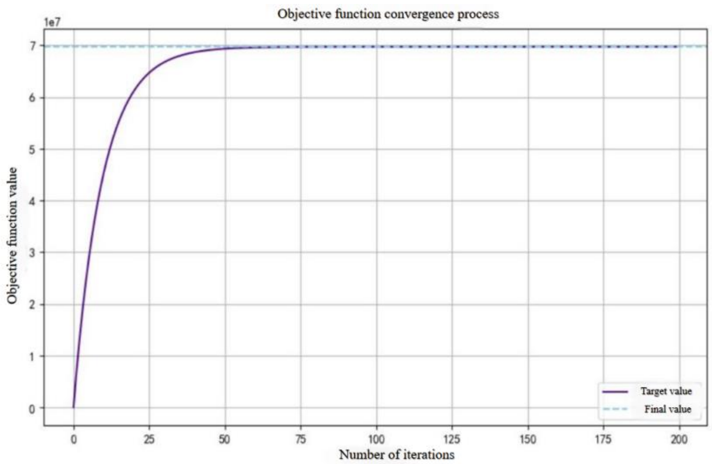

Figure 3. Neural network model solution results

It can be seen from the figure that the number of times required for the objective function iteration to reach the final target value is greatly increased compared with the Monte Carlo model solution, and the final target value is far ahead of the value solved by the two optimization algorithms. When the number of iterations reaches 50, the convergence of the objective function tends to the limit, indicating that the optimization process is over, the simulated crop planting income reaches the maximum, and the optimization effect is excellent.

3.4 Discussion of results

Through the model test, it is found that the neural network model is faster than the simulated particle swarm optimization algorithm and Monte Carlo model in the optimization problem of crop yield maximization. The comparison results are summarized in Table 1. Through the in-depth analysis of these data, the intelligent optimization algorithm can accurately predict the growth trend and income status of crops, provide timely and accurate decision support for farmers, further reduce agricultural production costs and improve economic benefits.

Through the application of intelligent optimization algorithms, it is possible to build a smart agriculture platform that integrates data collection, analysis and decision-making, which helps promote the development of agriculture in the direction of intelligence and information technology, and improve the scientific and technological content and competitiveness of agricultural production.

Table.1. Comparison results of three algorithms

Comparison	Number of iterations	Final value
Simulation particle swarm optimization model	38	-0.73
Monte Carlo model solving	20	-2.48
Neural network model solving	62	7

4. Conclusions

In this paper, three intelligent optimization algorithms are used to optimize the crop planting scheme

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and find the best crop planting scheme to maximize the crop planting benefit. However, relying only on the data of 2023 as a reference to make future predictions, and not considering the extreme fluctuations in yield per mu and fluctuations in sales, costs, etc., will affect the accuracy of the model. In the future, we will continue to optimize the model, improve the accuracy of the model, and make the results more reliable.

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