Eurasia Journal of Science and Technology
Print ISSN: 2663-1024
Online ISSN: 2663-1016
DOI: https://doi.org/10.61784/ejst3109

OPTIMAL CROP PLANTING STRATEGY BASED ON PARTICLE SWARM ALGORITHM

TianYou Zuo[1*], LiangYing Ji[2], YuSa Liu[3]
[1]Department of School of Overseas Education, Changzhou University, Changzhou 213164, Jiangsu, China.
[2]Department of School of Safety and Engineering, Changzhou University, Changzhou 213164, Jiangsu, China.
[3]Department of College of pharmacy, Changzhou University, Changzhou 213164, Jiangsu, China.
Corresponding Author: Tianyou Zuo, Email: 15961207191@163.com

Abstract: With the development of rural economy, optimizing planting strategy is an important research topic in organic planting industry. At present, most experts are not clear about the binding conditions for crop planting. This paper searched for data on agricultural products and local soil conditions in Hutang Town, Changzhou City, Jiangsu Province, and identified data on local cropping strategies for 2023. Based on the above data and the ideas of linear programming and multi-objective programming, the planting strategy optimization model under multiple constraints was established by determining planting risk factors and other indicators to seek the optimal crop planting strategy with maximum returns, and particle swarm optimization algorithm was used to solve the model. Finally, the optimal planting strategy under certain conditions and uncertain factors is obtained, and the complex problems arising from the optimal crop planting strategy are solved.
Keywords: Linear programming; Monte carlo simulation; Poisson process; Particle swarm optimization

1 INTRODUCTION

With the development of rural economy, the issue of optimizing planting strategies is an important research topic in the organic farming industry. Obtaining optimal crop planting strategies has become more difficult under many changing cropping conditions and policy economics.
Prof. Xu Zhihong of the University of Chinese Academy of Sciences and others pointed out in his article “The Development Status and Future Trends of Chinese Agriculture” that the adjustment of agricultural planting strategies is very complex and should be adjusted to the trend, but did not give a specific strategy in the context of the actual situation[1]. In other articles, they propose a proposal for optimizing crop planting strategies under specific natural conditions such as climatic and soil conditions in the Sichuan region, but in practice the influence of humanistic conditions on planting strategies is very important, and the above mentioned article did not specify the changes that these conditions may bring to the planting strategies[2].Some teams made a more detailed combination of natural and human factors on the impact of planting strategy for analysis, and we found that in practice there are some uncertainties such as sudden natural disasters on the cultivation of the judgment of the interference, which we believe that we need to add[3].
Therefore, we combine the natural and human conditions of crop cultivation and stochastic simulation of uncertainties to construct a more accurate model of crop cultivation strategies.
After model building and solving, this paper derives the local crop planting strategy for the next seven years. This makes up for the lack of integration of natural factors, human factors and uncertainties into the model building in the above literature, which better maximises crop revenue, improves farmers' economic income and positively affects local economic growth. Finally, we make a comprehensive evaluation of the proposed model, and consider that the model in this paper fits the reality, can reasonably solve the proposed problems, and has the characteristics of strong practicability and high efficiency of algorithm. The model is also applicable to forestry, animal husbandry and other aspects.

2 RELATED THEORIES

2.1 Monte Carlo Simulation

The Monte Carlo method, also known as statistical simulation, is a stochastic simulation method, a computational method based on probabilistic and statistical theoretical methods, and an approach to solving many computational problems using random numbers (or, more commonly, pseudo-random numbers). The problem to be solved is linked to a certain probabilistic model, and statistical simulation or sampling is implemented using an electronic computer to obtain an approximate solution to the problem.
When the problem to be solved is the probability of occurrence of a certain event, or the expected value of a certain random variable, they can obtain the frequency of occurrence of this event, or the average value of this random variable, by means of a certain “test” method, and use them as a solution to the problem. The Monte Carlo method is a numerical simulation of an experiment by capturing the geometric quantities and geometric features of the motion of a thing and

simulating them mathematically[4]. It is based on a probabilistic model and follows the process depicted in this model, by simulating the results of the experiment as an approximate solution to the problem. Monte Carlo problem solving can be reduced to three main steps: constructing or describing the probabilistic process; realizing sampling from a known probability distribution; and establishing various estimators[5].

2.2 The Particle Swarm Optimization

Particle swarm algorithm is an optimization algorithm based on group intelligence, and its basic idea originates from the study of the foraging behavior of bird flocks, by initializing the particle swarm, evaluating the fitness of each particle, and initializing the individual optimum and the global optimum. Repeat the above steps to update the individual optimal and global optimal until the global optimal solution is found and output, which is mainly used to solve continuous nonlinear optimization problems.

Assuming that there is a D-dimensional target search space with n particles forming a particle swarm, where each particle is described by a D-dimensional vector, denote its spatial location as $m_i = (m_{i1}, m_{i2}, \cdots, m_{iD})$, $i = 1, 2, \cdots, n$; This can be viewed as a solution in an objective optimization problem, and substituting the fitness function to calculate the fitness value can measure the merit of the particles; the flight speed of the ith particle is also a D-dimensional vector, denoted as $v_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$[6].The position experienced by the ith particle with the best fitness value is called the best position in the history of the individual and is denoted as $p_i = (p_{i1}, p_{i2}, \cdots, p_{iD})$: The best position experienced by the entire particle population is called the global historical best position, denoted as $p_g = (p_{g1}, p_{g2}, \cdots, p_{gD})$, The evolutionary equation for a swarm of particles can be described as follows[7].

$$v_{ij}(t+1) = v_{ij}(t) + c_1 r_1(t)\big(p_{ij}(t) - x_{ij}(t)\big) + c_2 r_2(t)\big(p_{gj}(t) - x_{ij}(t)\big) \tag{1}$$

$$m_{ij}(t+1) = m_{ij}(t) + v_{ij}(t+1) \tag{2}$$

Where i denotes the ith particle, j denotes the jth dimension of the particle, t denotes the tth generation, and c_1, c_2 are two acceleration constants that usually take values in the range (0,2), $r_1 \sim U(0, 1)$, $r_2 \sim U(0, 1)$ are two mutually independent random functions[8]. From the above equation, we see that c_1 regulates the particle to go to the best position in its own neighborhood, and c_2 regulates the particle to go to the best position that can be found by the whole swarm of particles.

2.3 The Poisson Process

The Poisson distribution is one of the most important discrete distributions, and it occurs mostly in occasions such as when X denotes the number of events that occur in a certain time or space[9].

Assuming that natural disasters will occur k times over a long period of time 0-τ, take a very large natural number n and divide the time period 0-τ into equal n segments:

$$l_1 = \left[0, \frac{1}{n}\right], l_2 = \left[\frac{1}{n}, \frac{2}{n}\right], \ldots, l_i = \left[\frac{i-1}{n}, \frac{i}{n}\right], \ldots, l_n = \left[\frac{n-1}{n}\right] \tag{3}$$

Make the following two assumptions:

1. The probability of a natural disaster occurring exactly once in every l_i is approximately proportional to the length of this period of time, $\frac{1}{n}$, which can be set to $\frac{\gamma}{n}$. When n is large, $\frac{1}{n}$ is small, and it is impossible for two or more natural disasters to occur in such a short period of time as l_i. Therefore the probability that a natural disaster does not occur during a period of time l_i is $1 - \frac{\gamma}{n}$.
2. The segments $l_i, \ldots, l_n$ are independent when it comes to whether a natural disaster occurs or not.

Set each small segment to be $\delta = \frac{\tau}{n} (n \to \infty)$, where the probability that k natural disasters may occur in time δ is $P(k, \delta)$, then:

$$P(k, \delta) = \begin{cases} 1 - \lambda\delta & k = 0 \\ \lambda\delta & k = 1 \\ 0 & k > 0 \end{cases} \tag{4}$$

The probability that a natural disaster occurs k times in n subsections is then:

$$C_n^k P^k (1-p)^{n-k} \qquad P = \lambda\delta \tag{5}$$

$$e^k = \lim_{n\to\infty} \left(1 + \frac{k}{n}\right)^n \tag{6}$$

In turn, a Poisson process is used to model the probability of occurrence of a natural disaster, and this probability is used as a planting risk factor to influence the objective function[10].

3 EXPERIMENT

The model fully considers the impact of expected sales volume, planting cost, mu yield and other factors on planting strategy, and lists a total of 19 constraints on the model according to the requirements of different aspects of the constraints to ensure the accuracy and reliability of the model. Monte Carlo simulation is introduced to simulate the planting cost, mu yield and other decision variables with a small range of uncertainty. For the potential planting risk, this paper introduces the concept of planting risk factor, which is obtained in the form of probability according to the Poisson process, and constructs the linear relationship between the factor and the objective function, so as to satisfy the simulation of the planting risk affecting the return. As the increase in the number of constraints increases the model complexity, this paper increases the number of iterations when choosing the particle swarm optimization algorithm to solve the problem, so as to make the model results closer to the optimal results. The particle swarm algorithm flow is shown in Figure 1.

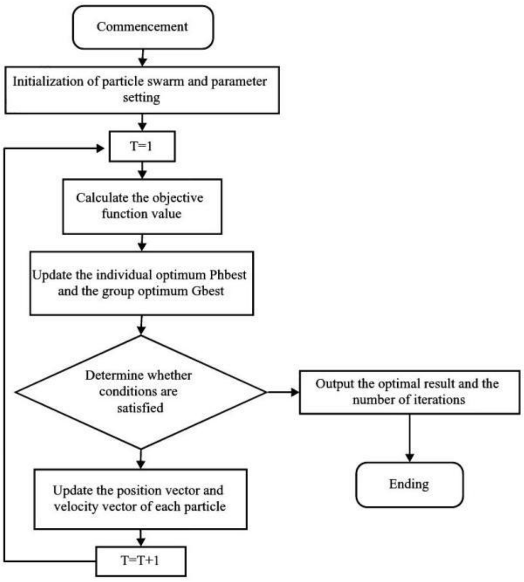

Figure 1 Particle Swarm Optimization Algorithm Model Illustration

According to the crop cultivation data in the Hutang Town area of Changzhou City that we have found, this paper derives the following objective function:

$$\max\left\{\sum_{k=1}^{2}\sum_{i=1}^{N}\sum_{j}\sum_{t}\left[x_{ijkt}S_j(t)P_j(t)D_j(t)\right]-\sum_{k=1}^{2}\sum_{i=1}^{N}\sum_{j}\sum_{t}x_{ijkt}C_i\,(t)\right\}[\,-P(k,\tau)+1\,] \tag{7}$$

Included among these:

x_{ijkt} denotes the area of crop j planted in plot i in the kth season in year t;i∈ [1, ...N]:denotes plot I;j∈ [1, ...M]:denotes the jth crop;t is the planting year and t∈ T = {2024,2025,2026...2030};D_j is the expected sales volume;P_j is the acre yield of each crop, and;C_j is the cost of cultivation;S_j is the selling price;T is the type of planting;A_j is the total area of the jth plot or shed.

Combined with the data related to specific practical conditions, this paper gives the following constraints:

$$\text{st.}\begin{cases} D_i(t)=D_i(2023)\cdot\left(1+r_{i,t}\right),\ r_{i,t}\in[0.05,0.10],\ \forall i\in\{C_6,C_7\},t\in\{2024,\dots,2030\}\\ D_i(t)=D_i(2023)\cdot\left(1+r_{i,t}\right),\ r_{i,t}\in[-0.05,0.05],\ \forall i\notin\{C_6,C_7\},t\in\{2024,\dots,2030\}\\ p_i(t)=p_i(2023)\cdot\left(1+u_{i,t}\right),\ u_{i,t}\in[-0.1,0.1],\ \forall i,t\in\{2024,\dots,2030\}\\ c_i(t)=c_i(2023)\cdot(1+0.05)^{t-2023},\forall i,t\in\{2024,\dots,2030\}\\ s_i(t)=s_i(2023),\ \forall i\text{ with }S_i=S_1\cup S_2,t\in\{2024,\dots,2030\}\\ p_i(t)=p_i(2023)\cdot(1+0.05)^{t-2023},\ \forall i\text{ with }S_i=S_3\cup S_4,t\in\{2024,\dots,2030\}\\ p_i(t)=p_i(2023)\cdot\left(1-v_{i,t}\right),\ v_{i,t}\in[0.01,0.05],\ \forall i\text{ with }S_i=S_5,t\in\{2024,\dots,2030\}\\ p_{41}(t)=p_{41}(2023)\cdot(1-0.05)^{t-2023},\ t\in\{2024,\dots,2030\}\end{cases} \tag{8}$$

The optimal strategy for crop cultivation in Hutang Town, Changzhou City, in the next seven years was derived by solving the above model using particle swarm optimization algorithm. The details are as follows.

4 RESULTS

In solving the above model, this paper adopts the particle swarm optimization algorithm, and after simulating through many iterations, it comes up with the planting strategies of different crops in the next 7 years, in which this paper selects the planting strategy in 2024 for displaying.

As shown in the table below, Table 1 indicates particle swarm optimization model parameters, and Table 2 indicates Selected results of crop cultivation distribution in 2024.

Table 1 Particle Swarm Optimization Model Parameters

Parameter description	Parameter values	Parameter description	Parameter values

Inertial Weight	0.5	Particle Number	30
Individual Learning Factor	1.5	Maximum number of iteration	5000
Social learning Factor	1.5	Monte Carlo simulations	100

Table 2 Selected Results of Crop Cultivation Distribution in 2024

Area number	Crop name	Area size (acres)	Planted area (acres)
A1	Broomcorn	80	72.3
A2	Barley	55	55.0
B1	Refried beans	60	59.3
B2	Barley	46	42.0
C1	Buckwheat	15	14.7
D7	Kidney bean	15	15.0
E1	Mushrooms	0.6	0.3
E2	Morel mushrooms	0.6	0.3
F2	Capsicum	0.6	0.3

Based on the adjustment of the above particle swarm parameters (as shown in Table1), some results of crop planting strategies were derived (as shown in Table2). Based on the above crop planting strategies, this paper concludes that the total crop income in the local area in the next 7 years is about 20 million yuan.

5 CONCLUSIONS

In this paper, we have fully considered the factors affecting the planting strategy such as expected sales volume and planting cost, and listed a total of several constraints to impose different forms of restrictions on the model as required. We introduced Monte Carlo simulation to simulate decision variables such as planting cost and mu yield with a small degree of uncertainty. For potential planting risk, we introduced the concept of planting risk factors and calculated the factors in probabilistic form using Poisson process.

Eventually, a crop cultivation strategy for the next seven years in Hutang Town, Changzhou City was derived. The output of the model meets the requirements of the topic and can solve practical problems. The particle swarm optimisation algorithm used in this paper has the characteristics of high stability and strong global search ability, which is very suitable for solving complex multi-objective optimisation models. The model can be more widely promoted. In the field of animal husbandry, the parameter of the number of livestock breeds can be used to replace the parameter of the planting area of agricultural products, so as to solve the problem of the optimal breed purchase strategy under limited economic conditions.

COMPETING INTERESTS

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

REFERENCES

[1] Xu Zhihong, Sun Caixin, Zhang Xiaoxing, et al. The Development Status and Future Trends of Chinese Agriculture. Transactions of China Electrotechnical Society, 2021, 19(10): 53-58.

[2] Fangfang. Analysis of Crop Cultivation Techniques and Factors Affecting High Yield. Harbin Institute of Technology, 2022, 34(2): 57-63.

[3] Ma Xuesong. Comprehensive data: area under cultivation of major crops and trends in China. IEEE Transactions on Power Systems, 2021, 16(4): 798-805.

[4] Ma Kunlong. Monte Carlo and Quasi-Monte Carlo Methods. Changsha: Hunan University, 2020, 6(1):107-115.

[5] Shen Xianjun. Adaptive particle swarm optimisation algorithm and its applications. Systems Engineering-Theory and Practice, 2022, 30(1): 158-160.

[6] Tang Guosheng. Particle swarm and applications. Journal of Higher Education, 2023, 9(11): 53-56.

[7] Liu Zhimei. Deep integration of Mathematical Modeling and Mathematics Teaching in Higher Vocational Colleges. Journal of Jiamusi Vocational College,2023, 39(03):152-154.

[8] Xu Yatao, Wu Libao. Research on Evaluation index system of Mathematical modeling teaching in Senior high school based on Delphi AHP. Journal of neijiang normal college, 2023, 38(02): 113-119.

[9] Yang Benchao, Shi Yaan, Duan Ganheng, et al. Analysis of price fluctuation of agricultural products in China and its influencing factors. University Education, 2023(04): 44-46.

[10] Huang Jian, Xu Binyan. Research on crop production risk management based on Monte Carlo simulation. Journal of Mathematics Education, 2020, 32(01): 93-98.