Research on Optimal Crop Planting Strategy Based on Multi-Factor Perturbation in North China Mountain Village

Feifan Chen *,†, Zhixiang Zhuang †

Department of computer, North China Electric Power University (Baoding), Baoding, China, 071003

* Corresponding Author Email: cff202210@163.com

† These authors contributed equally.

Abstract. Agriculture is an important part of the national economy, and crop cultivation is the cornerstone of sustainable agricultural development. As the main production place of crops in the countryside, it is of great significance to formulate appropriate crop planting strategies for the sustainable development of rural economy. A sustainable agricultural crop cultivation model can fully utilize land and water resources, increase farmers' income, and achieve sustainable agricultural development. There are many factors that influence crop growing strategies, such as climate and market conditions. This paper establishes an optimal planting model for crops under multi-factor perturbation based on historical data and comprehensive consideration of various uncertainties and potential planting risks. We use Monte Carlo simulation to model the uncertainties, and use integer planning model and simulated annealing algorithm to deal with the crop planting problem in the two cases respectively, deriving the optimal cultivation strategy for the mountainous countryside in North China.

Keywords: Agricultural Cultivation, Integer Programming, Simulated Annealing Algorithm.

1. Introduction

Agriculture is a vital component of the national economy, and effective crop planting strategies are crucial for enhancing profitability and achieving sustainable development [1]. The growth cycle of crops is long and subject to numerous uncertainties, such as climate change and market fluctuations [2]. Traditional static planting planning methods often fail to address these challenges effectively, resulting in suboptimal economic potential for certain farmlands [3].

This study focuses on villages located in the mountainous regions of North China, which are characterized by diverse terrain, variable soil types, and distinct seasonal variations in crop production. Data sources include local records on farmland types, planting seasons, crop yields per unit area, planting costs, crop sale prices, and total planting areas from 2010 to 2023. These datasets provide comprehensive insights into the region’s agricultural production and form the basis for model development.

In recent years, researchers have proposed innovative methods, such as multi-objective optimization models and dynamic programming, to address the complexities of crop planting. However, these methods have notable limitations, including insufficient consideration of long-term climate change and environmental impacts [4], high computational complexity that hinders practical application, and limited research on planting strategies under multi-factor perturbations, particularly those integrating market demands and environmental constraints [5].

To address these gaps, this study introduces several novel approaches. First, it incorporates a multi-factor perturbation model that integrates uncertainties such as climate, market demand, and crop yield, thereby enhancing the robustness of crop planting strategies [6]. Second, the concept of "virtual partitioning" is proposed to optimize land allocation and crop rotation strategies, improving land use efficiency [7]. Furthermore, the adaptability of planting strategies to uncertainties is analyzed and validated using Monte Carlo simulations and simulated annealing models [8, 9]. Finally, this study develops an optimization model centered on profit maximization while also accounting for environmental sustainability and socio-economic impacts [10].

Through these methodologies, this research aims to provide scientifically grounded and adaptable solutions for crop planting strategies, promoting sustainable agricultural development and achieving a balance between economic and environmental benefits.

2. The basic fundamental of integer programming

2.1. The structure of integer programming

Integer programming model is an important branch of mathematical planning that require decision variables to take on integer values (usually 0, 1, 2, ... and other integers) and not arbitrary real numbers. This model solves optimization problems by maximizing or minimizing an objective function while satisfying a set of equations or inequality constraints.

The optimization problem consists of three basic elements, which are:

(1) Decision variables: factors that can be controlled by the decision maker. Depending on the actual problem, the decision variables can be selected as the output of the product, the amount of material shipped and the number of days worked.

(2) Objective function: It is a function to represent the goal pursued by the decision maker. For example, the objective may be to maximize profit or minimize cost, etc.

(3) Constraints: the qualifications to be met by the decision variables.

2.1.1 Definition of decision variables

For illustrative purposes, we use Table 1 to show the defined decision variables. Among them, mu is Chinese unit of land measurement that is commonly 666.7 square meters. Yuan, represents the standard unit of money used in the People's Republic of China.

Table 1. Definition of decision variables

notation	clarification	unit
$X_{i,j}^t$	area planted with crop i in year t on site j	mu
S_j^t	cultivated area of type j land in year t	mu
$P_{i,j}$	unit price of sale of crop i in place j	yuan/catty
$Y_{i,j}$	expected sales of crop i at site j	mu/catty
$C_{i,j}$	cost of planting the i-th crop in the j type of land	yuan/mu
$A_{i,j}$	yield of the i-th crop at the j type of land acre	catty
$D_{i,j}^{t-1}$	total area of plots belonging to type j plots planted in year t-1 for crop i	mu
W_1^t	total crop profits in year t	yuan

2.1.2 Establishment of objective function

The optimization objective is to make the crop planting profit maximum, so we establish the objective function based on the maximization of revenue:

2.1.3 Description of constraints

$$Maximize\ W_1^t = \sum_{j\in H}\sum_{i=1}^{n}\left(P_{i,j}\cdot\left(\min\left(Y_{i,j},\, A_{i,j}\cdot X_{i,j}^t\right) - \sum_{j\in H}\sum_{i=1}^{n}\left(C_{i,j}\cdot X_{i,j}^t\right)\right)\right. \tag{1}$$

There are three constraints for all types of cropland:

I. Each crop should not be planted on too small an area in a single plot.

II. Each crop cannot be planted in the same plot in consecutive heavy crops.

III. The sum of the acreage of all individual products planted on a type of land does not exceed the total acreage of that type of land.

Given that different cropland types grow different crops, planting is done using the idea of compartmentalization, i.e., for different cropland types are treated separately. Specific constraints for each type of cropland are given below:

For hillsides, flat drylands, terraces:

I.

$$\{X_{i,j}^{t} \geqslant Minarea\} \cup \{X_{i,j}^{t} = 0\} \tag{2}$$

Where Minarea is minimum planting area per crop per individual plot. Minarea = 0.3 acres when the cropland type is barnyard and Minarea = 1.0 acres when it is a non-barnyard type.

II.

$$X_{i,j}^{t} \leqslant \max\left(S_{j}^{t} - D_{i,j}^{t-1}, 0\right) \tag{3}$$

III.

$$\sum_{i=1}^{n} X_{i,j}^{t} \leqslant S_{j}^{t} \tag{4}$$

For watered land:

I.

$$\{X_{i,j}^{t,K} \geqslant Minarea\} \cup \{X_{i,j}^{t,K} \geqslant 0\} \tag{5}$$

K=1 indicates the first season and K=2 indicates the second season.

II.

$$X_{16}^{t} \leqslant S_{j}^{t} - D_{16,j}^{t-1} \tag{6}$$

III.

$$\sum_{20 \leqslant i \leqslant 34} X_{i,j}^{t} + X_{16,j}^{t} \leqslant S_{j}^{t} \tag{7}$$

$$\sum_{35 \leqslant i \leqslant 37} X_{i,j}^{t} + X_{16,j}^{t} \leqslant S_{j}^{t} \tag{8}$$

For ordinary greenhouses:

I.

$$X_{i,j}^{t,K} = 0.3m, m = 0, 1, 2 \ldots \tag{9}$$

II.

$$X_{i,j}^{t,\ 2} = \max\left(S_{j}^{t,2} - D_{i,j}^{t,1}, 0\right) \tag{10}$$

$$X_{i,j}^{t,\ 1} = \max\left(S_{j}^{t,1} - D_{i,j}^{t-1,2}, 0\right) \tag{11}$$

III.

$$\sum_{20 \leqslant i \leqslant 34} X_{i,j}^{t} \leqslant S_{j}^{t} \tag{12}$$

$$\sum_{38 \leqslant i \leqslant 41} X_{i,j}^{t} \leqslant S_{j}^{t} \tag{13}$$

2.2. Principles of the simulated annealing algorithm

Simulated annealing algorithm is a heuristic algorithm that simulates the cooling of solids in nature. Its basic idea is to start from a higher initial temperature, along with the continuous decline of temperature parameters, combined with a certain probability of jump characteristics in the solution space to randomly find the global optimal solution of the objective function, that is, in the local optimal solution can probabilistically jump out of the final convergence of the global optimum.

2.2.1 Metropolis Guidelines

The Metropolis criterion is how to make a local optimal solution jump out in the case of a local optimal solution and is the basis of the algorithm. That is, accepting new states with probability, rather than using fully deterministic rules.

Assuming that the previous state is A, the system changes its state to B according to a certain indicator (gradient descent, energy of the previous section). Accordingly, the energy of the system changes from $f(A)$ to $f(B)$, the probability of acceptance p_t of the system from changing is defined as:

$$p_t = \begin{cases} 1, & f(A) < f(B) \\ e^{-(f(A)-f(B)) \times C_t}, & f(A) \geqslant f(B) \end{cases} \tag{14}$$

2.2.2 Steps for simulating annealing algorithm

Step1) Given an initial temperature $t=100$, a temperature decay coefficient $\alpha=0.95$, randomly generate an initial state $s=s_0$. Let $k=0$, with a maximum of 100 iterations per temperature;

Step2) Each time the planting area of the current solution is fine-tuned, a new state $s_j = Genete(s)$ is produced;

Step3) if $\min\left\{1, \exp\left[-\frac{c(s_j)-c(s)}{t_k}\right]\right\} \geqslant random[0,1]$, then $s=s_j$.

Step4) until the sampling stability criterion is satisfied: de-temper $t_{k+1} = updata(t_k)$ and let $k=k+1$;

Step5) until the algorithm termination criterion is satisfied: output the algorithm search results.

The flowchart of the algorithm is shown in Figure 1.

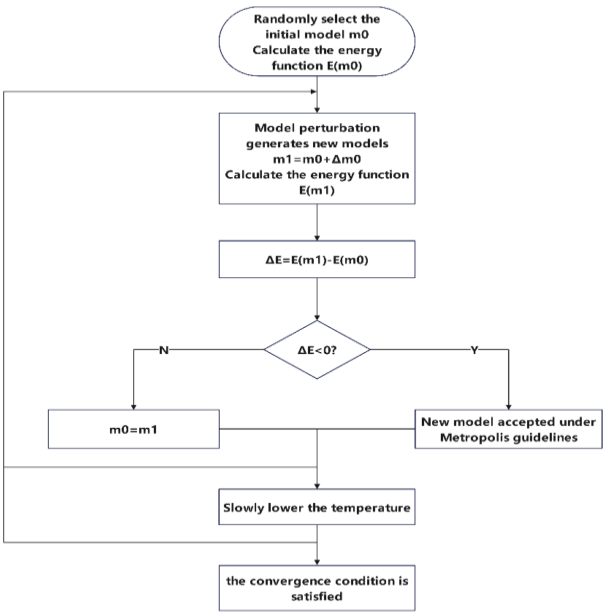

Figure 1. Flowchart of simulated annealing algorithm

3. Results

3.1. The establishment of simulation model

Using MATLAB toolbox to solve, the planting area of each individual product on various types of cultivated land is shown in Table 2.

According to Table 2, in terms of crops, soybean among the legume crops has the largest acreage of 109 acres in Site B in 2024. Wheat has the largest area under food crops, followed by cereals and maize. In terms of the type of cultivated land, the largest area under cultivation in site A is maize and the smallest is cereals; The largest area is planted with cereals and the smallest with barley in Site B. More common greenhouse morels, elm yellow mushrooms, and white ling mushrooms are planted.

Table 2. Total acreage of individual products in different cropland types in 2024

kind / geotype	soya bean	black bean	red bean	mung bean	climing bean	wheat	corn	millet
A	23	41	0	41	5	110	128	2
B	109	0	58	28	15	109	5	182
C	1	3	1	30	5	0	0	4
	broomcorn millet	buckwheat	pumpkin	sweet potato	naked oat	barley		
A	3	0	6	3	0	0		
B	0	0	6	14	35	1		
C	23	15	0	0	0	20		
	cowpea	blade bean	kidney bean	potato	tomato	eggplant	spinach	capsicum annuum
D	11	13	1	15	11	6	0	1
E	0.9	0.9	0.9	0	3	0.6	0	0
F1	0	0	0	0	0.3	0.3	0.3	0
F2	0	0	0	0	0	0	0	0
	cabbage	lettuce	baby bok choy	cucumber	celery	capsicum	water spinach	chard
D	0	0	10	0	0	0	0	0
E	0.6	0.6	0.6	0.6	0	0.3	0	0
F1	0	0	0.3	0.3	0	0	0	0.3
F2	0.3	0.3	0	0	0.3	0.3	0.3	0
	Chinese cabbage	Raphanus sativus longipinnatus	radish	shaggy ink capsule	mushroom	white mushroom	morel mushroom	maize
D	14	19	12	0	0	0	0	19
E	0	0	0	1.8	0.6	1.8	2.4	0
F1	0	0	0	0	0	0	0	0
F2	0	0	0	0	0	0	0	0

Note: F1 indicates Smart Shed Season 1, F2 indicates Smart Shed Season 2

3.2. Analysis of experimental results

The acreage of each individual product planted in each plot resulting from the MATLAB toolbox is shown in Table 3.

According to Table 3, the largest acreage of corn, 108 acres, and the smallest acreage of sorghum, 5 acres, were planted in the Type A site. The largest area of millet is cultivated in type B land, followed by soybean and wheat. And the most green beans were planted in the C-type plot at 24 acres; soybeans were not planted.

Table 3. Planted area of each individual product in each plot in 2024

kind / geotype	soya bean	black bean	red bean	mung bean	climbing bean	wheat	corn	millet	common sorghum
A1	0	0	0	0	3	0	61	0	0
A2	16	27	10	2	0	0	0	0	0
A3	0	0	0	0	3	20	0	3	0
A4	0	0	0	0	4	0	47	5	5
A5	0	0	0	0	6	51	7	0	0
A6	5	10	0	38	0	0	0	0	0
B1	0	0	0	0	7	0	3	44	0
B2	0	0	0	0	6	0	0	0	40
B3	0	0	0	0	1	32	2	0	0
B4	0	0	0	0	0	0	0	2	0
B5	0	0	0	0	0	0	0	0	0
B6	71	6	1	8	0	0	0	0	0
B7	26	10	7	12	0	0	0	0	0
B8	10	4	5	10	0	0	0	0	0
B9	0	0	0	0	0	0	0	42	0
B10	0	7	10	8	0	0	0	0	0
B11	0	0	0	0	0	0	0	34	0
B12	0	0	0	0	0	27	0	0	2
B13	0	0	0	0	1	16	0	0	0
B14	0	0	0	0	4	0	0	3	0
C1	0	0	0	0	3	0	7	0	0
C2	0	10	1	2	0	0	0	0	0
C3	0	0	0	0	0	5	0	0	2
C4	0	0	0	0	1	0	0	0	0
C5	0	0	5	22	0	0	0	0	0
C6	0	0	0	0	0	0	0	2	0

Use EXCEL to calculate the profit from crop cultivation from 2024 to 2029 as Table 4:

Table 4. Crop planting profit from 2024 to 2029

vintage	2024	2025	2026	2027	2028	2029
Profit (ten thousand yuan)	581.31	609.28	564.09	543.22	618.50	730.62

According to Table 4, the average profit from 2024 to 2029 is RMB 6,078,400 with a standard deviation of 66.31. In terms of data trends, profits fluctuated up and down over the years and did not show a steady increasing or decreasing trend. Despite the fluctuations, the data points are relatively concentrated and there are no outliers far from the overall trend. This suggests that profits from crop farming in the village may be affected by some common factors, such as climate and market demand, but have remained somewhat stable overall. This indicates that the crop cultivation strategy in this countryside has some market potential and risk-resistant ability.

4. Conclusion

This study initially employed integer programming to simulate crop planting scenarios under ideal conditions, optimizing resource allocation through precise mathematical models to achieve anticipated economic benefits and environmental sustainability goals. This approach allowed us to gain insights into the optimal distribution of resources such as land, water, and fertilizers, ensuring maximum productivity while minimizing environmental impact.

However, recognizing the frequent impact of various uncertain factors on agricultural production, such as climate change, market demand fluctuations, pests and diseases, as well as other potential disturbances, we further incorporated the Monte Carlo simulation method to construct an environmental model that integrates multi-factor perturbations. This model enabled us to assess the robustness of our planting strategies under a wide range of scenarios, including extreme weather events, market crashes, and pest outbreaks.

Within this framework, simulated annealing techniques were utilized to deeply explore agricultural production under non-ideal conditions. These techniques allowed us to refine our planting strategies by iteratively testing and adjusting them based on feedback from the simulation results, ultimately leading to more resilient and adaptable farming practices.

Experimental results demonstrate that the model proposed in this study not only successfully maximizes economic returns but also ensures environmental sustainability. Our model displayed strong adaptability, as it was able to maintain high productivity even when faced with significant disruptions. Furthermore, the practical application value of our model was showcased through its ability to provide actionable insights for farmers and policymakers, enabling them to make more informed decisions about resource allocation and farming practices.

By overcoming the limitations of traditional methods in handling uncertainty and balancing computational efficiency with adaptability, this study provides significant insights for sustainable agricultural development. It highlights the immense potential of advanced computational models in improving agricultural practices in the face of multifaceted challenges, such as climate change, market volatility, and emerging pests and diseases. Our findings suggest that the integration of integer programming, Monte Carlo simulation, and simulated annealing techniques can lead to more resilient, sustainable, and profitable farming practices, ultimately contributing to the long-term sustainability of agricultural systems.

References

[1] Johnson, K., Davis, P. Cost-efficient crop planning [J]. Journal of Agricultural Science, 2022, 160 (6): 451-463.

[2] Wei, J., Sun, K. Climate-resilient agriculture [J]. Environmental Research Letters, 2023, 18 (1): 014-025.

[3] Adenso-Díaz, B., Lozano, S. Production planning under demand uncertainty [J]. Journal of Operations Research, 2020, 34 (5): 789-803.

[4] Cai, C., et al. Crop rotation optimization under uncertain market demands [J]. Sustainability, 2024, 12 (3): 847-860.

[5] Zhou, Z., Liu, X. Risk management in crop planting strategies [J]. International Journal of Agricultural Economics, 2020, 14 (3): 167-179.

[6] Li, X., Wang, J. Monte Carlo simulation for agricultural planning under climate uncertainty [J]. Applied Mathematical Modelling, 2023, 89 (1): 123-140.

[7] Smith, R. A., Chen, Y. Optimization of agricultural supply chains [J]. Computers and Industrial Engineering, 2022, 159: 107-123.

[8] Harrison R L. Introduction to monte carlo simulation [C] // AIP conference proceedings. NIH Public Access, 2010, 1204: 17.

[9] Haddock J, Mittenthal J. Simulation optimization using simulated annealing [J]. Computers & industrial engineering, 1992, 22 (4): 387-395.

[10] Liu, F., et al. Dynamic programming for crop planning [J]. Agronomy Journal, 2021, 113 (6): 4571-4580.