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ANALYSIS OF CROP PLANTING STRATEGIES USING IMPROVED SIMULATED ANNEALING OPTIMIZATION ALGORITHM

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Abstract: Given the actual needs of farmers and the need to protect the environment, selecting suitable crop optimization planting strategies is of great significance. Based on the analysis of the impact of different types of land parcels on crop yield, crop rotation demand, and market demand changes, this article optimizes the allocation of arable land resources through an improved simulated annealing algorithm. Determine the indicators based on the given data and use the Stackelberg model to calculate the selling price, establish a single objective optimization model, and solve for the optimal planting results through an improved simulated annealing algorithm. Firstly, visualize the data to understand the features and determine the indicators, and use the Stackelberg model to calculate the selling price. Secondly, construct a single objective optimization model based on indicators and constraints. Finally, in order to simplify the calculation and improve the accuracy of the optimal solution, the plot is divided into four parts, and a preliminary solution is obtained through simulated annealing algorithm. Then, an adaptive threshold is introduced to improve the optimal planting strategy. This indicates that the improved simulated annealing algorithm can obtain the optimal solution for multiple crop planting strategies under different unsold models, demonstrating that the improved simulated annealing algorithm has made good progress in solving related crop planting strategies.
Keywords: Optimization strategies for crop cultivation; Improve simulated annealing algorithm; Single objective optimization model; Optimal planting strategy

1 INTRODUCTION

As a large agricultural country with high cross regional, China has complex types and quantities of farmland plots. Under the background of the deepening of agricultural refinement and marketization, it is of great significance to realize the development of rural economy and revitalize the countryside how to use different types of farmland and multiple crops for rational distribution in order to obtain the maximum economic benefits.

A large number of studies have been carried out at home and abroad on the optimization of annual crop planting strategies. Not only the optimization methods are designed, but also the greedy heuristic algorithm is used to solve the problem of crop planting in the division of management areas in specific locations[1]; Some scholars use the improved neural network model to carry out a reasonable overall planting strategy for crops[2]; At the same time, the comparative advantage model is constructed for crop planting strategies in different geographical regions[3]; J. B.nixon and other scholars studied the optimal crop planting strategy in Western Kansas through the decision support system (dssat-csm) model. At the same time, some scholars have studied, such as corn[4], wheat[5], rice[6]. In addition, multi crop coupling research[7]. Rabbani M scholars use the entropy weight method-TOPSIS method combined with a two-stage optimization approach to optimize crop planting strategies[8]; Wu Hui scholars use ArcGIS spatial analysis and other methods to explore the changes in optimizing the relationship between water[9], land, energy, economy, environment, and food; simultaneously, Wang Chang and others scholars conduct research on the optimal planting strategy based on the NSGA-II algorithm[10]; Bellangue D emphasizes that the development of ranch economy is driven by integrating market prices to achieve the optimal crop planting strategy[11].

Through literature review and theoretical research, it is believed that the optimization of agricultural planting system forms a complex coupling network in the interaction of crops, cultivated land types and previous crops. Existing studies have confirmed that the scientific allocation of planting proportion of different crops can significantly improve the output value per unit area, but there are still research gaps in the spatial heterogeneity of cultivated land types, the dynamic matching mechanism of previous crops and the global optimization algorithm under multiple constraints. This paper constructs a multi-dimensional classification system based on multiple types of crops and heterogeneous cultivated land types, which breaks through the traditional single category classification model. By establishing a single objective optimization model with constraints of land carrying capacity and crop rotation, and innovatively combining neighborhood search strategy with annealing mechanism, an adaptive threshold algorithm with dynamic step size adjustment is designed.

2 MULTI CROP PLANTING PLAN AND INDICATOR CONSTRUCTION

2.1 Establishment of Farmland Types and Agricultural Product Production Indicators

The type of cultivated land, as a limiting factor for agricultural production and a major influencing factor for planting selection, results in different types of cultivated land cultivating different crops [7]. By preprocessing the data, we construct indicators for farmland types and agricultural product production:

2.1.1 Farmland type indicator (S_k)

The cultivated land type index classifies cultivated land into six types: flat dry land (A), terraced fields (B), hillside land (C), irrigated land (D), as well as ordinary greenhouses (E) and smart greenhouses (F). And different types of cultivated land produce different products, so cultivated land is represented as flat dry land S_1, terraced land S_2, hillside land S_3, irrigated land S_4, ordinary greenhouse S_5, smart greenhouse S_6, and the formula is given:

$$S_1 = [s_{1,1}, s_{1,2} \dots s_{1,6}] \tag{1}$$

The above six types of cultivated land are represented by S_k; $s_{k,n}$ represents the nth plot of land in the k category.

2.1.2 Agricultural product planting rate index (X_k (t))

The planting rate of agricultural products is a numerical reflection of the value of intercropping. Referring to the influence of intercropping of agricultural products, the planting rate index of agricultural products is used to determine the quantity of agricultural products planted. Among them, flat dry land (A), terraced land (B), and hillside land (C) are planted once a year, so their crop planting indicators meet the following requirements:

$$\sum_{j=1}^{l_k} x_{k,i,j}(t) = 1, (k = 1,2,3) \tag{2}$$

Among them, l_k is the kth cultivated land type that can be used as the number of crops for planting; $X_{k,\,i,\,j}\,(t)$ are the kth cultivated land type and the jth agricultural product planting rate of the i land. The ordinary greenhouse (E) and the smart greenhouse (F) are planted twice a year, and there is a significant difference in the second quarter between the ordinary greenhouse and the smart greenhouse. Therefore, they respectively meet the following requirements:

$$\sum_{j=1}^{l_{k,1}} x_{k,i,j,1}(t) \le 1 \quad (k = 5) \tag{3}$$

$$\sum_{j=1}^{l_{k,2}} x_{k,i,j,2}(t) \le 1 \quad (k = 5) \tag{4}$$

$$\sum_{j=1}^{l_k} x_{k,i,j}(t) \le 2 \quad (k = 6) \tag{5}$$

Among them, $l_{k,\,1}$ is the type of crop planted in the first season of Class E farmland; $l_{k,2}$ As a type of crop planted in the second season of Class E arable land.

$$\sum_{j=1}^{l_k} x_{k,i,j}(t) \le 1 \quad (k = 4), \tag{6}$$

Among them, $X_k\,(t)=[x_{k,\,1}\,(t),\, x_{k,\,2}\,(t) \dots x_{k,\,i}\,(t)]$ is used as the indicator of agricultural product planting rate.

2.1.3 Agricultural product yield indicator (S_kH_k (t))

The yield per mu of agricultural products reflects the production volume of agricultural products. Due to the consideration of intercropping, the yield per mu of a single agricultural product may not accurately reflect the actual planting capacity. Therefore, the agricultural product planting rate index is used to solve the problem:

$$H_k(t) = X_k(t)N_k(t) \tag{7}$$

Among them, N (k) is the crop yield per mu of the k type of land in the t year. So the total yield $S_kH_k\,(t)$of each cultivated land type can be calculated as an indicator of agricultural product yield.

2.1.4 Cost index per mu of agricultural products (α_k(t))

The cost per acre of agricultural products is used as production cost, which is an additional expense incurred during the production of agricultural products. It has already been given in the question, so definition $\alpha_{k,\,i,j}(t)$. Using a single agricultural product cost index for matrix transformation as $\alpha_k\,(t)$ to obtain the cost index per mu of agricultural products.

2.2 Establishment of Sales Prices and Expected Sales Volume Indicators for Agricultural Products

The selling price and sales volume of agricultural products are the source of farmers' income and the only way in which agricultural products can provide value. As an important part of determining the sales price and sales volume of agricultural products and constructing crop planting strategies.

2.2.1 Expected sales volume indicator of agricultural products (D (t))

The expected sales volume of agricultural products is an important basis for producing agricultural products, and it is also a reasonable control of the production quantity of agricultural products during production; Using the quantity of agricultural products produced in 2023 as the expected sales volume for agricultural products for calculation:

$$d_j(t) = \sum_{i=1}^{81} h_{k,i,j} \tag{8}$$

Where $d_j\,(t)$ is the expected sales volume of the j crop planted in the t year; $H_{k,\,i,\,j}$ are the quantities of the *j* crop grown on the *i* land of the *k* type of cultivated land in 2023. Using $d_j\,(t)$ to form a new matrix function yields:

$$D(t) = [d_1(t), d_2(t), \dots, d_j(t)] \tag{9}$$

As the final calculation function for the expected sales volume of agricultural products.

2.2.2 Agricultural product sales price index (P_k (t))

The selling price of agricultural products, as a floating price, is often difficult to measure intuitively. Using the Stackelberg game theory, a game analysis is conducted on consumers and producers of agricultural products to obtain a price function .

Considering that consumers desire lower prices for agricultural products; Being a leader in the agricultural product market. Using the buyer's price acceptance ability as the pricing standard, referring to the commonly used value λ=0.8 as the purchasing function, the sales price is obtained:

$$U(p_{k,j}(t)) = p_{k,j,max}(t) - 0.8(p_{k,j,max}(t) - p_{k,j,min}(t)) \tag{10}$$

Among them, $U(\cdot)$ is the utility function used as a price indicator for calculation; $p_{k,j,max}(t)$ is the highest price per kilogram of the *j* crop planted in the *k* type of cultivated land in the *t* year; $p_{k,j,min}(t)$ is the lowest price per kilogram of the *j* crop planted in the *k* type of cultivated land in the *t* year. Substitute the above formula into the price matrix to obtain $P_k(t)$ as the indicator of agricultural product sales price:

$$P_k(t) = [p_{k,1}(t), p_{k,2}(t), \dots p_{k,j}(t)] \tag{11}$$

3 CONSTRUCTION OF OBJECTIVE FUNCTION FOR CROP PLANTING STRATEGY

3.1 Construction of a Model for Unsold Waste

The type of cultivated land, as a limiting factor for agricultural production and a major influencing factor for planting selection, results in different types of cultivated land cultivating different crops. By preprocessing the data, we construct indicators for farmland types and agricultural product production:

The unsold waste model is a control strategy for agricultural product yield based on expected sales volume indicators. The following are the steps for building a function:

Step 1. Construction of crop profit function

Determine the planting rate and production cost of each crop to establish a simple crop profit function:

$$Q_k = S_k H_k(t) P_k(t) - S_k X_k(t) \alpha_k(t) \tag{12}$$

Where Q_k represents the profit amount of the k type of farmland; $S_k H_k(t)$ calculates the crops produced on the k type of farmland. Further accumulation of the function gives the profit amount for each type of farmland:

$$Q = \sum_{k=1}^{6} [S_k H_k(t) P_k(t) - S_k X_k(t) \alpha_k(t)] \tag{13}$$

Among which $\sum_{k=1}^{6} S_k H_k(t)$ refers to all crops produced from the cultivated land.

Step 2. Calculation of Unsold Waste

By calculating based on the number of unsold and wasted items:

$$u_j(t) = max[(\sum_{k=1}^{7} S_k H_k(t))_j - d_j(t), 0] \tag{14}$$

Among them, $u_j(t)$ is the excessive planting amount of the crop at time t; Max [f, 0] is the judgment function, and when f>0, the value of *f* is taken; On the contrary, take 0 as the numerical value; Substitute $U_j(t)$:

$$U(t) = [u_1(t), u_2(t) \dots u_{41}(t)] \tag{15}$$

U (t) is the stagnant sales volume of agricultural products in year t.

Step 3. Introduction of the unsold waste function

The profit function for crops will deduct the excess portion of the crops.

$$Q(t) = \sum_{k=1}^{6} (S_k H_k(t) P_k(t) - S_k H_k(t) \alpha_k(t)) - U(t)P(t). \tag{16}$$

Thus, the preliminary unsold waste function is constructed.

Step 4. Limiting Function Determination

The restrictions on crops are mainly divided into planting season restrictions and restrictions on crop rotation and the planting of leguminous crops. The planting season restrictions have been addressed in the agricultural planting rate indicators. Now, the restrictions on crop rotation and the planting of leguminous crops are being established:

$$\sum_{j=1}^{l_k} x_{k,i,j,1}(t) + x_{k,i,j,2}(t) \leq 1 \quad (k = 6) \tag{17}$$

$$\sum_{j=1}^{l_k} x_{k,i,j}(t) + x_{k,i,j}(t+1) \leq 1 \quad (k = 1,2,3)\ . \tag{18}$$

$$\sum_{t=n}^{n+2} \sum_{j=1}^{l_{k,1}} s_{k,i} x_{k,j}(t) \geq 1 \tag{19}$$

Among them, l_k represents the number of crops that can be planted on the *k* type of farmland; $x_{k,i,j,1}(t)$ is the yield of the *j* type of crop in the first season for the *i* plot of the *k* type of farmland at time *t*; $x_{k,i,j,2}(t)$ is the yield of the *j* type of crop in the second season for the *i* plot of the *k* type of farmland at time *t*. $l_{k,1}$ represents the number of the first *j* types of leguminous crops for the *k* type; $x_{k,j}(t)$ is the planting rate of crop *j* in the *k* type of farmland at year *t*. Considering that it is not advisable to disperse a crop too much within a single plot, a concentration index is used to manage the degree of dispersion:

$$\beta_{k,j}(t) = \frac{\sum_{i=1}^{n_k} (s_{k,i} x_{k,j}(t))^2}{(\sum_{i=1}^{n_k} s_{k,i} x_{k,j}(t))^2} \geq 0.6 \tag{20}$$

Among them, $\beta_{k,j}(t)$ is the dispersion of type j crops in class k cultivated land at time t. Finally, the model of unsold waste is obtained mould:

$$max \quad W = \sum_{t=1}^{7} Q(t) = \sum_{t=1}^{7}\sum_{k=1}^{6}\left[S_k H_k(t)P_k(t) - S_k X_k(t)\alpha_k(t)\right] - \lambda U(t)P(t).$$

$$s.t\begin{cases}\sum_{j=1}^{l_k} x_{k,i,j}(t) = 1 (k=1,2,3)\\ \sum_{j=1}^{l_{k,1}} x_{k,i,j,1}(t) \le 1 \quad (k=5)\\ \sum_{j=1}^{l_{k,2}} x_{k,i,j,2}(t) \le 1 \quad (k=5)\\ \sum_{j=1}^{l_k} x_{k,i,j}(t) \le 2 \quad (k=6)\\ \sum_{j=1}^{l_k} x_{k,i,j,1}(t) + x_{k,i,j,2}(t) \le 1 \quad (k=6)\\ \sum_{j=1}^{l_k} x_{k,i,j}(t) + x_{k,i,j}(t+1) \le 1 \quad (k=1,2,3)\\ \sum_{t=n}^{n+2}\sum_{j=1}^{l_{k,1}} s_{k,i}\, x_{k,j}(t) \ge 1\\ \beta_{k,j}(t) = \frac{\sum_{i=1}^{n_k}(s_{k,i}x_{k,j}(t))^2}{(\sum_{i=1}^{n_k} s_{k,i}\, x_{k,j}(t))^2} \ge 0.6\end{cases} \tag{21}$$

Here, n represents the seasonal indicator for a year of planting. When n = 1, it is considered the first season; when n = 2, it is considered the second season.season at that time; it was considered as the second season at that time.

3.1.1 Construction of the unsold inventory price reduction model

The unsold goods markdown model has undergone a partial change in its objective function compared to the unsold goods waste model. The original function $-U(t)P(t)$ has been modified to $-0.5U(t)P(t)$,resulting in a new optimal crop planting plan model. The parameter $\lambda=0.5$ is substituted as part of the unsold goods markdown model.

3.2 Simulated Annealing Algorithm and Improvements

For solving the linear strategy objective function, due to the large amount of variable data and numerous constraints, the simulated annealing algorithm can be used to solve the data. However, the simulated annealing algorithm struggles to eliminate the influence of many small plots, so new optimization constraints need to be added for algorithm improvement:

Step 1. Finding the initial solution

Use the raw data from 2023 as the initial solution for function value processing.

Step 2. Randomly generate a new solution that meets the constraint conditions

Calculate the fitness of the new solution and use the Metropolis criterion to accept worse solutions with a certain probability, in order to prevent getting stuck in a local optimal solution for agricultural product planting, and to find the global optimal solution for agricultural product planting. The function is set as:

$$p = \alpha_L e^{-|W_{great} - W_L|} \quad (W_{great} \ge W_L) \tag{22}$$

$$p = 1 \quad (W_{great} < W_L). \tag{23}$$

Among them, p represents the probability of accepting W_{j+1}; L is the number of iterations; Wgreat is the optimal solution value; W_L is the value at the L iteration. α_L is the decay function at the L iteration.

In order to prevent the local optimal solution from being unable to reach the global optimal solution due to the rapid decline of the decay function, after reviewing the literature and discussing with the team, it is concluded that a decay coefficient of α=0.95 is optimal.

Step 3. Improved Segmentation Calculation Using Simulated Annealing Algorithm

Due to the long runtime of the simulated annealing algorithm in practical data processing, further model simplification is required. From the problem analysis after constructing the aforementioned annealing algorithm, it can be understood that the types of crops planted differ according to different land types and planting frequencies. These can be divided into four main categories: grain crops planted on flat dry land (A), terraced fields (B), and hilly land (C); vegetable crops (excluding Chinese cabbage, white radish, and red radish) planted in the first season of irrigated land (D), ordinary greenhouses (E), and smart greenhouses (F); Chinese cabbage, white radish, and red radish planted in the second season of irrigated land (D); edible fungi crops planted in the second season of ordinary greenhouses (E). Additionally, the unsold waste model must account for rice production crops in irrigated land (D) with one season per year. Thus, the unsold waste model and the unsold price reduction model for agricultural products are divided into four main categories and solved separately.

Step 4. Improvement of Adaptive Threshold in Simulated Annealing Algorithm

The use of the dispersion function cannot perfectly control the spatial dispersion of crop planting. There still exists a situation where crops are planted in dispersed areas of the same type of farmland. It is necessary to further reduce the impact of crop planting dispersion and introduce a dispersion function optimization to minimize the planting dispersion caused by the simulated annealing algorithm.

Determine the adaptive threshold for the simulated annealing algorithm:

$$O(L) = 0.1 - 0.05e^{-L}. \tag{24}$$

Among them, $O(L)$ is the judgment function after the L iteration. When the planting rate of a single crop in the planting area is less than $O(L)$, the crop is excluded, and the planting rate is reallocated to the remaining crops:

$$x_{k,i,j}(t) = \frac{x_{k,i,j}(t)}{\sum_j \ x_{k,i,j}(t)}. \tag{25}$$

The simulated annealing algorithm resolves the issue of scattered planting in crop cultivation, while also providing the optimal crop planting plan.

4 MODEL SOLUTION RESULTS

4.1 Unsolved Overstock Waste Model Solution Results

By applying the improved simulated annealing algorithm to the unsold waste model, the optimal solutions for the segmented types were obtained. The final iteration results are shown in Figure 1:

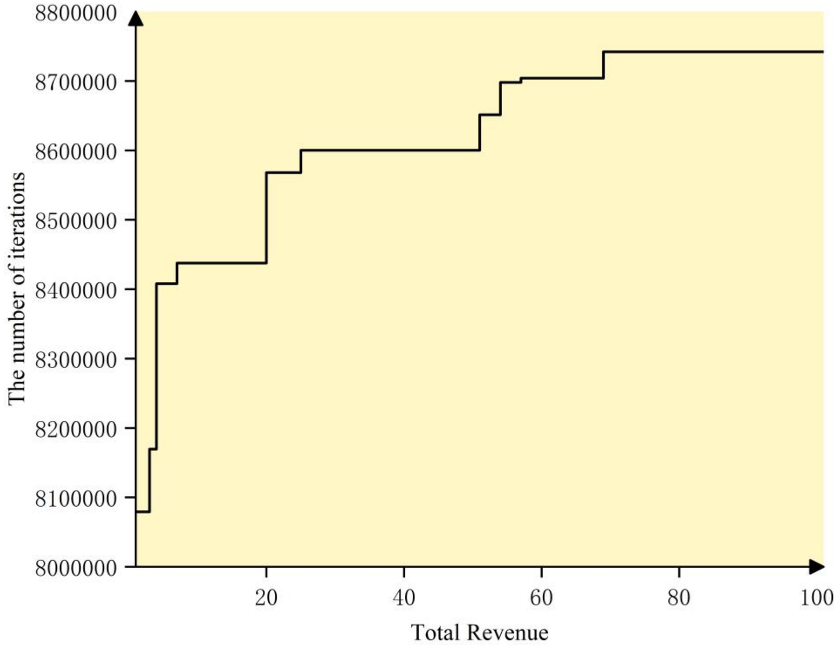

Figure 1 Simulated Annealing Algorithm for the Unsold Waste Model of Vegetable Crop Planting Iteration Revenue

The remaining iteration results; the final solution gives a total income of 26,473,326.43 yuan for the years 2024-2030.

4.2 Results of the Unsold Stock Price Reduction Model

By incorporating the improved simulated annealing algorithm into the unsold product markdown model, the optimal solution for each segmented type is obtained. The final iteration results are shown in Figure 2:

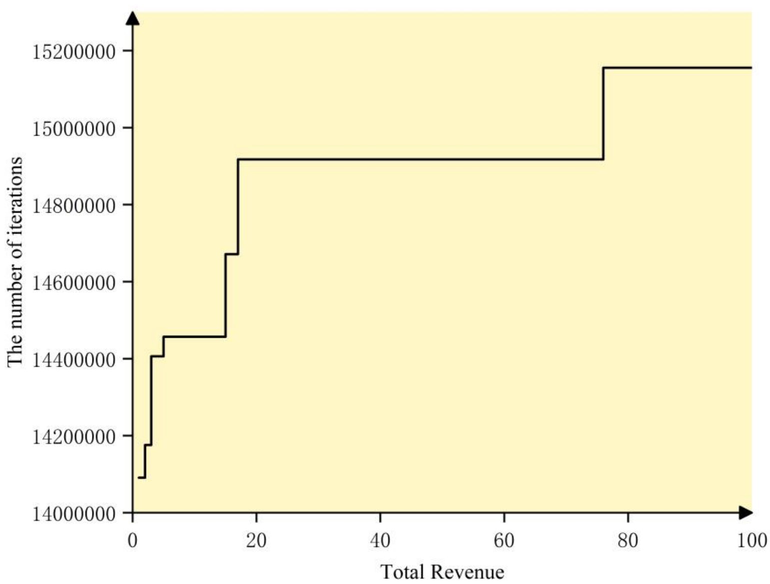

Figure 2 Simulated Annealing Algorithm for Slow-moving Price Reduction Model in Vegetable Crop Planting Iterative Profit

The remaining iterative results; the final solution yields a total income of 35,402,395.67 yuan for the years 2024-2030.

The final planting result is shown in Figure 3:

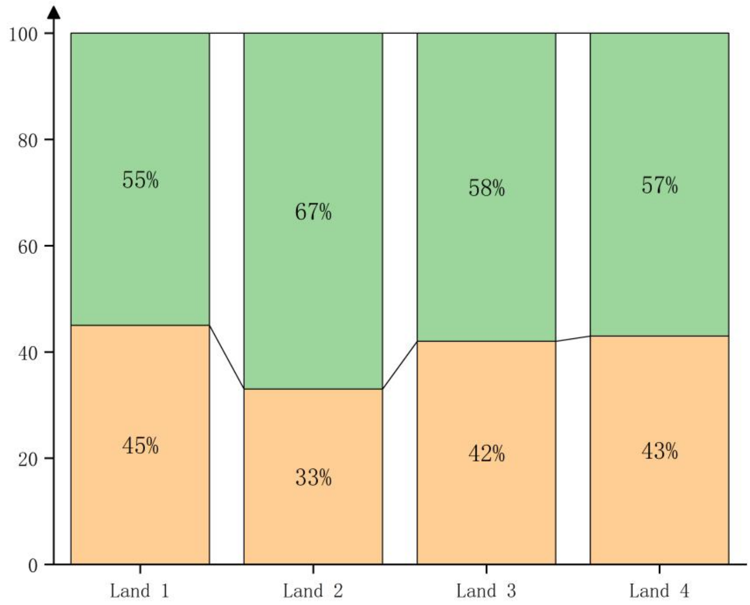

Figure 3 Comparison of Sales Volume between the Slow-Moving Discount Model and the Slow-Moving Waste Model

From Figure 3, it can be concluded that the unsold goods discount model enables the cultivation of more agricultural products to maximize income. In subsequent problem-solving, the unsold goods discount model will be used as the foundational model for improving crop cultivation strategies.

5 CONCLUSION

This article is based on the types of farmland for crop cultivation and the equations for crop yield and sales price indicators. It aims to construct an objective function for crop planting strategies and establishes a structural optimization model between multiple crops and multiple pieces of farmland. An improved simulated annealing algorithm with an adaptive threshold algorithm was designed to solve the model. The model was then applied to 1,201 acres of farmland, divided into 34 plots of varying sizes, for validation. The following conclusions were drawn:

a) The calculation results show that the unsold waste model indicates the actual agricultural output has already exceeded market demand. This result reflects that current agricultural production is sufficient to meet the general market demand. On the other hand, the unsold price reduction model proposes a solution that is more beneficial for agricultural profitability, increasing rural income, and promoting higher economic value for rural areas.

b) Traditional genetic algorithms, particle swarm algorithms, and simulated annealing algorithms have wide applications, but their actual computation time and accuracy are relatively low. By specifically adjusting and improving the simulated annealing algorithm, text integrate the complex constraint conditions with the process of generating new solutions in the algorithm, ultimately deriving the optimal planting strategy under the constraint conditions. This not only overcomes the issues of low accuracy, long convergence time, and difficulty in obtaining the optimal solution in the previous code, but also adds more practical value and significance to the proposed multi-crop planting plan.

c) The example calculation results indicate that under different types of unsold goods processing conditions, the improved simulated annealing algorithm can obtain the optimal solution for the overall model performance within the allowed error of the iteration, suggesting that the algorithm is widely applicable to crop planting strategy models.

Based on the budget provided by the above model, the following agricultural planting recommendations are given:

a) It is recommended to adopt a dynamic crop rotation mechanism, based on the planting rate index $X_k(t)$ generated by the simulated annealing algorithm, combined with the seasonal carrying capacity characteristics of the cultivated land type S_k. Priority should be given to deploying crops such as corn and wheat in flat dry lands (A) and terraced fields (B), utilizing their storage tolerance characteristics to balance the risk of unsold crops.

b) Implement the 'Rice + Fast-growing Vegetables' intercropping model in the irrigated area (D). In the first season, rice is planted to meet the basic food demand, and in the second season, a sales slump and price reduction model is used to guide the planting of cabbage-type crops with short growth cycles and high price elasticity, creating a differentiated planting sequence.

c) Establish an IoT-based agricultural product market forecasting system that updates the expected sales volume $D(t)$ and sales price $P_k(t)$ indicators in real time. Integrate sensor monitoring data with an improved simulated annealing algorithm to dynamically optimize the value range of the λ parameter ($0.5 \leq \lambda \leq 1$), and create a flexible mechanism for handling slow-moving goods.

d) Regarding the issue of scattered land plots for cultivation, it is recommended that local governments promote the construction of 'concentrated contiguous planting areas.' By facilitating land transfer, the concentration index $\beta_{k,j}(t)$ can be enhanced, ensuring that the dispersion of crops on similar types of arable land remains within the optimized range where $\beta_{k,j}(t) \geq 0.8$. This will help reduce the complexity of algorithmic solutions;

e) Strengthen training on algorithm applications for agricultural cooperatives, establish a digital twin model incorporating parameters from 34 plots, and regularly simulate planting strategy scenarios, with a particular focus on the dual-season planting constraints of k=6 types of cultivated land (smart greenhouses). This includes ensuring that $x_{6,i,j,1}(t) + x_{6,i,j,2}(t) \leq 1$ for continuous annual production. Subsequent research can delve deeper into the dynamic impact mechanisms of climate change factors on the yield indicator $H_k(t)$, as well as the corrective effects of different regional government subsidy policies on the cost indicator $\alpha_k(t)$.

COMPETING INTERESTS

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

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