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Multi-stage Crop Planting Strategy optimization Model Based on PSO Algorithm

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***Abstract*—This paper presents a multi-stage crop planting strategy optimization model utilizing the Particle Swarm Optimization (PSO) algorithm. The model aims to address key challenges in agriculture, such as fluctuating market demands, climate variability, and rising production costs. Over a seven-year planning horizon (2024-2030), the model dynamically adjusts crop planting strategies by integrating factors like crop yield, market prices, and crop rotation. The proposed framework optimizes both crop selection and area allocation to maximize economic profitability while maintaining sustainable practices. Unlike traditional static models, this approach accounts for uncertainties and adapts to real-time changes in market conditions. The model's ability to adjust planting strategies based on PSO ensures that farmers can optimize yields and reduce waste through flexible decision-making. Experimental results demonstrate the model's effectiveness in dynamically optimizing planting strategies while satisfying constraints such as land availability and crop rotation.**

Keywords: optimization Model; Crop Planting; mathematics modeling; multi-stage optimization; PSO

I. Introduction

The production of foodstuffs for human consumption is a fundamental aspect of global food security. However, this sector is confronted with a number of significant challenges, including climate change, unpredictable market demands and fluctuating production costs. In this context, the optimization of crop planting strategies assumes great importance, in order to guarantee both economic viability and sustainability. The majority of traditional crop planning approaches rely on historical data or static models, which are unable to adapt to the inherent uncertainties associated with climate and market fluctuations[1-3].

II. Related Work

Marius et al. proposed a multi-objective model for agricultural crop planning in 2011, considering weather risk, market risk and environmental risk. They proved that the minimum environmental risk problem is equivalent to a mixed-integer problem with a linear objective function[4]. Ángel et al. proposed a multi-stage linear programming model for planting plan decisions under the new Common Agricultural Policy in 2019, determining the planting plan that maximises net income within a given time frame[5].

Multi-stage optimization models have been used in a variety of agricultural contexts to deal with uncertainties in market demand, environmental change and resource allocation. Traditional optimization techniques, such as linear programming, are designed to maximise short-term profits. However, they lack the flexibility to deal effectively with long-term fluctuations in yield and demand.

More recent approaches, such as particle swarm optimization (PSO) and dynamic programming, have been integrated to facilitate continuous adjustment to market changes.Yubao et al. established a water-saving planting structure optimization model in 2019 by combining multi-objective chaotic particle swarm optimization algorithm (MOCPSO) with chaos technology[6]. Oscar et al. established a milk production optimizer that combines weather dynamics in the same year with the ability to deeply analyse the interrelationships between weather and price uncertainty on decision-making[7].

Although multi-objective optimization methods have been proposed in previous studies, the impact of multi-stage uncertainty is rarely considered in complex planting environments, such as the diverse terrain in northern China. The multi-stage optimization model proposed in this paper integrates various factors such as climate change, market price fluctuations, crop rotation requirements, and land use restrictions to dynamically adjust planting strategies. The particle swarm optimization algorithm achieves the dual optimization objectives of crop yield and economic benefits in fluctuating environments, ensuring that planting strategies can adapt to constantly changing market and environmental conditions.

III. Methods

A. Problem Formulation

The crop planting strategy has been devised with the objective of optimising crop selection and area allocation over a seven-year period (2024-2030) on the basis of crop yield, planting costs and market prices. In formulating this strategy, due consideration has been given to the potential for uncertainty in future demands and production costs. The model comprises three principal components.

Crop yield prediction: The model indicates that annual yield fluctuations are likely to occur within a range of ±10%.

Planting cost projection: This calculation is based on the assumption of a 5% annual increase in planting costs.

Market price variability: The market prices of vegetables are modelled with a growth rate of 5%, whereas those of mushrooms, including shiitake, are modelled with a decrease of 1-5%.

B. *Multi-stage Optimization Framework*

Objective Function.

The profit $R_{ij}(t)$ for a given crop j in year t is computed as:

$$R_{ij}(t) = \min(Y_j \times A_{ij}, E_{ij}) \times P_j + \max(0, Y_j \times A_{ij} - E_{ij}) \times 0.5 \times P_j - C_j \times A_{ij} \tag{1}$$

Where:

Y_j is the crop yield per unit area,

A_{ij} is the area planted with crop j,

E_{ij} is the expected sales volume,

P_j is the market price of crop j,

C_j is the planting cost per unit area.

Constraints.

Land constraints: The total planting area for all crops must not exceed the available land area for each plot.

$$\sum_j A_{ij}(t) \leq A_{\text{total}} \tag{2}$$

Crop rotation: Each plot must rotate crops, and legumes must be planted at least once every three years to ensure soil health.

$$C_i(t) \neq C_i(t-1) \tag{3}$$

Market demand constraint: The total sales cannot exceed 80% of the predicted yield for each crop, ensuring some margin for unforeseen demand shortfalls.

The Multi-stage Optimization Framework algorithm can be found in Pseudocode 1.

Pseudocode 1 Multi-stage Optimization Framework

Objective: Maximize profit across all crops and years
procedure OPTIMIZECROPS($Y_j, P_j, C_j, A_{\text{total}}, E_{ij}$)
  for each year t **do**
    for each plot i **do**
      for each crop j **do**
        Compute profit $R_{ij}(t)$ using:
        $R_{ij}(t) \leftarrow \min(Y_j \times A_{ij}, E_{ij}) \times P_j + \max(0, Y_j \times A_{ij} - E_{ij}) \times 0.5 \times P_j - C_j \times A_{ij}$
      end for
      Apply constraints:
      Ensure $\sum_j A_{ij}(t) \leq A_{\text{total}}$ (Land constraints)
      Ensure $C_i(t) \neq C_i(t-1)$ (Crop rotation)
      Ensure total sales $\leq 0.8\times$ predicted yield for each crop (Market demand constraint)
      Optimize $A_{ij}(t)$ to maximize $\sum_j R_{ij}(t)$
    end for
  end for
end procedure

Pseudocode 1. Multi-stage Optimization Framework

C. *Particle Swarm Optimization (PSO) Application*

Given the high-dimensional nature of the problem, Particle Swarm Optimization (PSO) is used to dynamically adjust planting strategies over time. Each particle represents a potential planting strategy, and its fitness is evaluated based on the objective function. The algorithm iterates through potential solutions, updating positions and velocities based on the best-performing particles[8].

Key steps in the PSO algorithm include:

Initialization: Randomly initialize particle positions representing different crop planting areas.

Fitness Evaluation: Calculate the profit for each particle based on the objective function.

Update Rules: Update the position of each particle based on its personal best and the global best.

Iteration: Continue iterating until convergence or reaching a maximum number of iterations.

The specific steps of the Particle Swarm Optimization algorithm are shown in Pseudocode 2.

Pseudocode 2 Particle Swarm Optimization (PSO)

Require: N: Number of particles
Require: D: Dimension of the search space
Require: $V_{\max}$: Maximum velocity
Require: w: Inertia weight
Require: c_1, c_2: Acceleration coefficients
Require: $iter_{\max}$: Maximum number of iterations
Ensure: Best solution found
Initialize each particle's position $X_i = (x_i^1, x_i^2, \ldots, x_i^D)$ randomly
Initialize each particle's velocity $V_i = (v_i^1, v_i^2, \ldots, v_i^D)$ randomly
Evaluate the fitness of each particle $f(X_i)$
Set $P_{best,i} = X_i$ and $G_{best} = \arg\min_i f(X_i)$
for $iter = 1$ to $iter_{\max}$ **do**
  for $i = 1$ to N **do**
    Update the velocity v_i^d for each dimension d using:

$$v_i^d = w \cdot v_i^d + c_1 \cdot rand() \cdot (P_{best,i}^d - x_i^d) + c_2 \cdot rand() \cdot (G_{best}^d - x_i^d)$$

    Adjust v_i^d to be within $[-V_{\max}, V_{\max}]$
    Update the position $x_i^d = x_i^d + v_i^d$
    Evaluate the new fitness $f(X_i)$
    if $f(X_i) < f(P_{best,i})$ **then**
      $P_{best,i} = X_i$
    end if
    if $f(P_{best,i}) < f(G_{best})$ **then**
      $G_{best} = P_{best,i}$
    end if
  end for
end for
return G_{best}

Pseudocode 2. Particle Swarm Optimization

D. *Model Adjustments for Uncertainty*

To accommodate uncertain factors such as fluctuating market demands and changing production costs, the model adjusts planting areas dynamically each year. Crop yield and market price are adjusted according to observed trends and real-time data.

IV. RESULTS AND DISCUSSION

Our dataset comes from Contemporary Undergraduate Mathematical Contest in Modeling - 2024, which includes existing farmland in a given rural area, crops planted, crop planting situation in 2023 and sales data collected in 2023[9].

A. Experiment Setup and Data Preprocessing

To evaluate the performance and robustness of the multi-stage optimisation model, experiments were designed based on real data from 2023 to 2030. These experiments simulate planting strategies on different land types, market fluctuations and climate changes.

The dataset includes information on various crops such as wheat, soybeans and speciality crops such as shiitake mushrooms. Key data points include：

Yield per unit area (Y_j)

Planting costs per unit area (C_j)

Selling price per unit (P_j)

This article employs the Kolmogorov-Smirnov (K-S) test to ascertain whether a given dataset adheres to a normal distribution. The test entails a comparison between the empirical cumulative distribution function and the theoretical distribution, with the maximum difference between them being calculated. Should the difference be below the critical value, the data is deemed to align with the theoretical distribution. The single-sample K-S test is frequently employed to ascertain whether data adheres to a known distribution, with the null hypothesis being that the data originates from a one-dimensional continuous distribution F [10]. The test statistics are as follows:

$$Z = \sqrt{n}\max_i(|F_n(x_{i-1}) - F(x_i)|, |F_n(x_i) - F(x_i)|) \tag{4}$$

H is true, Z converges to the Kolmogorov-Smirnov distribution according to the distribution. That is, if the sample is taken from a one-dimensional continuous distribution F:

$$Z \to K = \sup|B(F(x))| \tag{5}$$

The outcome of a KS test is typically a p-value. If the p-value is less than the significance level (typically 0.05), the null hypothesis is rejected, indicating that the two samples are deemed to originate from disparate distributions.

Table 1. Data Preprocessing

indicator name	per mu yield	planting cost	sales price
test results	false	false	false

Therefore, for data that does not follow a normal distribution, we introduced a box plot to handle outliers. Box plot theory does not require data to follow a normal distribution and can intuitively describe the discrete distribution of data. It also provides a criterion for identifying outliers, where values greater than or less than the upper limit set in the box diagram are considered outliers.

The detection data should be sorted in ascending order, from $X_1, X_2, X_3, \cdots\cdots, X_n$, in order to obtain an ordered sequence. The median M is then calculated as follows:

$$\mathbf{M} = \begin{cases} X_{n+\frac{1}{2}}, \text{n is an odd number} \\ \frac{1}{2}\left(\frac{X_{\frac{n}{2}}}{2} + X_{1+\frac{n}{2}}\right), \text{n is an even number} \end{cases} \tag{6}$$

The criteria for determining outliers are:

$$X_1 > U + K \cdot IQR \mid X_1 < L - K \cdot IQR \tag{7}$$

In this context, the upper quartile point is represented by U, the lower quartile guard point is represented by L, the interquartile range is represented by IQR, the step size coefficient is represented by L, and the value of K is 1.5.

B. Experimental Procedure

The objective of this experiment is to conduct a comprehensive evaluation of two key scenarios. Primarily, the experiment seeks to optimise economic returns, taking into account market demand, production costs, and the evolving trends in crop sales prices from 2024 to 2030. Secondly, the experiment will also assess the efficacy of two distinct marketing strategies: one involves discarding the remaining products, while the other entails selling the remaining products at a 50% discount from the original price.

This article establishes several test cases to simulate various market and environmental fluctuations, and combines constraints to ensure comprehensive scenario analysis.

Yield fluctuation: ±10% variation in annual yield.

Market demand variation: ±5% for vegetable crops, 5-10% increase for staple crops such as wheat and corn.

Cost increase: 5% annual increase in planting costs.

Price trends: Vegetable prices increase by 5% annually, while specialty crop prices such as mushrooms decline by 1-5% annually.

Summary of model formulas

$$\text{Fitness}(X_i) = \sum_{t=1}^{T}\sum_{i=1}^{n}\sum_{j=1}^{m}\left[\min\left(Y_{j,t} \times A_{i,j,t}, E_{i,j,t}\right) \times P_{j,t} + \max\left(0, Y_{j,t} \times A_{i,j,t} - E_{i,j,t}\right)\right] \tag{8}$$

$$V_i(t+1) = \omega V_i(t) + c_1 r_1\left(P_{\text{best},i} - X_i(t)\right) + c_2 r_2\left(G_{\text{best}} - X_i(t)\right) \tag{9}$$

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{10}$$

C. Results and Discussion

Through iterative search using a particle swarm optimization algorithm, the planting plan corresponding to the global optimal solution G_{best} is the optimal planting strategy for each plot and season for the next seven years. The optimised planting plan includes crop types and planting areas for each plot and satisfies all planting constraints. The specific results are shown in Figures 1 and 2.

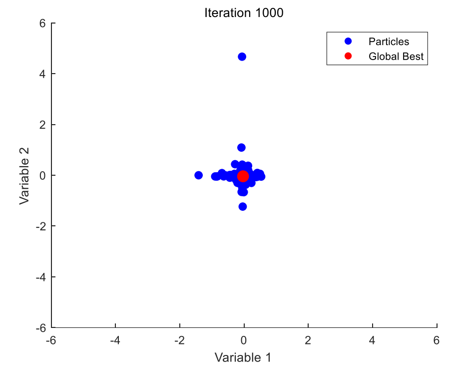

Figure 1. Global optimization solution after 1000 iterations

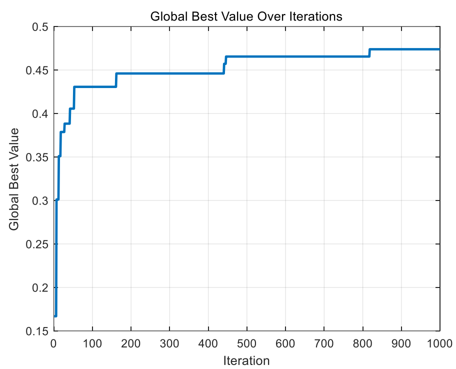

Figure 2. Global Best Value Over Iterations

The experimental results show that the multi-stage optimisation model effectively manages market and environmental fluctuations. Dynamic pricing and discounting of surplus products reduce waste and improve profitability. Crop rotation, integrated into a PSO-based model, ensures legumes are planted every three years, enhancing soil health, yield, and reducing fertiliser dependence.

Overproduction leads to significant profit loss, especially for crops with fluctuating demand, like mushrooms. However, selling surplus at a 50% discount boosts profitability. High-yield crops, such as wheat and shiitake mushrooms, benefit from reduced waste and flexible pricing, greatly increasing net profits.

Figure 3. PSO Training Loss Over Iterations

Figure 4. NSGA-II Training Loss Over Iterations

To further reinforce the research, this article also employed transfer learning, utilising the NSGA-II algorithm referenced in the GIS spatial optimisation research on agricultural crop allocation to resolve the objective function[11]. Following testing, after 1000 iterations of training, the mean training loss of PSO was found to be considerably lower than that of NSGA-II, as illustrated in Figures 3 and 4. This suggests that the PSO algorithm demonstrates efficacy in addressing specific problems analogous to those presented in this article.

V. CONCLUSIONS

This study proposes a multi-stage crop planting strategy optimisation model based on the particle swarm optimisation algorithm. By dynamically adjusting planting strategies to cope with uncertainties such as market demand fluctuations and environmental changes, this model successfully achieves a balance between economic profitability and sustainable agricultural practices. The integration of PSO enables adaptive decision-making, allowing farmers to optimise crop yields while respecting constraints such as crop rotation and land use restrictions. The flexibility of this model ensures that planting strategies can develop with changes in conditions, thereby maintaining long-term profitability. In the future, the integration of IoT intelligent sensors to monitor environmental factors could be considered, which would provide real-time data for the model and continue to optimise and promote the model.

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REFERENCES

[1] Jain R, Malangmeih L, Raju S S, et al. Optimization techniques for crop planning: A review[J]. The Indian Journal of Agricultural Sciences, 2018, 88(12): 1826-1835.

[2] Albornoz V M, Véliz M I, Ortega R, et al. Integrated versus hierarchical approach for zone delineation and crop planning under uncertainty[J]. Annals of Operations Research, 2020, 286: 617-634.

[3] Cid-Garcia N M, Ibarra-Rojas O J. An integrated approach for the rectangular delineation of management zones and the crop planning problems[J]. Computers and Electronics in Agriculture, 2019, 164: 104925.

[4] Rădulescu M, Rădulescu C Z, Zbăganu G. A portfolio theory approach to crop planning under environmental constraints[J]. Annals of Operations Research, 2014, 219: 243-264.

[5] Galán-Martín Á, Pozo C, Guillén-Gosálbez G, et al. Multi-stage linear programming model for optimizing cropping plan decisions under the new Common Agricultural Policy[J]. Land use policy, 2015, 48: 515-524.

[6] Wang Y, Wu P, Zhao X, et al. Water-saving crop planning using multiple objective chaos particle swarm optimization for sustainable agricultural and soil resources development[J]. CLEAN–Soil, Air, Water, 2012, 40(12): 1376-1384.

[7] Dowson O, Philpott A, Mason A, et al. A multi-stage stochastic optimization model of a pastoral dairy farm[J]. European Journal of Operational Research, 2019, 274(3): 1077-1089.

[8] Kennedy J, Eberhart R. Particle swarm optimization[C]//Proceedings of ICNN'95-international conference on neural networks. ieee, 1995, 4: 1942-1948.

[9] Contemporary Undergraduate Mathematical Contest in Modeling. https://www.mcm.edu.cn/

[10] Berger V W, Zhou Y Y. Kolmogorov–smirnov test: Overview[J]. Wiley statsref: Statistics reference online, 2014

[11] Krityakierne T, Sinpayak P, Khiripet N. GIS spatial optimization for agricultural crop allocation using NSGA-II[J]. Information Processing in Agriculture, 2024