Optimization Model for Crops Planting

Kailing Chen [#], Junxu Chen *

School of Economics and Management, North China Electric Power University, Baoding, 071003, China

* Corresponding Author Email: 15880063721@163.com

[#]These authors contributed equally.

Abstract. This study proposes a hybrid optimization model combining the Genetic Particle Swarm Algorithm (GPSO) with linear programming to optimize crop planting strategies under varying market conditions. The model incorporates price elasticity to estimate sales volumes and evaluates two scenarios: excess production leading to waste and excess production sold at a discount. By analyzing the results, our paper identifies optimal planting strategies for grains, legumes, vegetables, and edible fungi. Our findings reveal that crops with stable market demand, such as grains, are more suitable under conditions of excess waste, while high-value crops like edible fungi are preferable when excess production is sold at a discount. This research provides practical insights for agricultural planning, emphasizing the importance of market dynamics and crop-specific economic benefits.

Keywords: Objective Optimization, Genetic Particle Swarm Algorithm.

1. Introduction

Agricultural planning is a critical yet complex task that involves balancing multiple factors, including crop yields, market demand, soil fertility, and resource constraints. With the increasing volatility of agricultural markets and the growing need for sustainable farming practices, optimizing crop planting strategies has become a pressing challenge for farmers and policymakers alike.

Traditional approaches, such as linear programming and dynamic programming, have been widely used in agricultural optimization [1]. However, these methods often struggle to handle the high-dimensional and non-linear nature of real-world agricultural systems[2]. Recent advancements in metaheuristic algorithms, such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), have shown promise in addressing these challenges by combining global and local search capabilities [3]. The integration of GA and PSO, known as the Genetic Particle Swarm Algorithm (GPSO), has been successfully applied in various fields, including engineering design and resource allocation [4][5], but its application in agricultural optimization remains underexplored. Price elasticity plays a crucial role in determining crop profitability, as it reflects the responsiveness of sales volumes to price changes[6]. Studies have shown that incorporating price elasticity into agricultural models can improve the accuracy of sales volume estimates and optimize crop production [7][8]. Additionally, crop rotation and soil fertility are critical factors in sustainable farming practices, with research highlighting the importance of optimizing crop rotation schedules to maintain soil health and prevent pest outbreaks [9].

The main contribution of this study is as follows. (1) The model incorporates price elasticity to estimate expected sales volumes, offering a more realistic representation of market dynamics and enabling more accurate predictions of crop profitability under varying market conditions. (2)The study evaluates two distinct scenarios—excess production leading to waste and excess production sold at a discount—to identify optimal planting strategies, providing valuable insights into how different market conditions influence crop selection and planting decisions. (3) The findings offer practical guidance for farmers and policymakers by highlighting the importance of market dynamics and crop-specific economic benefits. (4)his study extends the application of GPSO to agricultural optimization, demonstrating its effectiveness in solving complex, real-world problems and providing a powerful tool for improving agricultural planning and resource allocation.

The structure of this paper is organized as follows. Section 2 reviews the theoretical foundations of the study, including objective optimization, the Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and the hybrid Genetic Particle Swarm Algorithm (GPSO). It also discusses the role of price elasticity in agricultural planning and the importance of crop rotation and soil fertility. Section 3 presents the proposed optimization model, including the formulation of decision variables, constraints, and the objective function. The model incorporates price elasticity to estimate sales volumes and evaluates two scenarios: excess production leading to waste and excess production sold at a discount. This section also describes the GPSO-based approach for solving the optimization problem. Section 4 discusses the experimental results, including the fitness curves and visualization of optimal planting strategies under the two scenarios. The analysis highlights the differences in crop yields and profitability, providing insights into the factors that influence optimal planting decisions. Finally, Section 5 summarizes the key findings of the study, discusses their implications for agricultural planning, and outlines potential directions for future research. The conclusions emphasize the importance of considering market dynamics and crop-specific economic benefits in optimizing crop planting strategies. By following this structure, the paper provides a comprehensive framework for optimizing crop planting strategies under varying market conditions, offering both theoretical insights and practical applications for agricultural planning.

2. Related Theories

Objective optimization is a fundamental concept in operations research, engineering, and computer science, aiming to find the best solution to a problem under given constraints. The goal is typically to maximize or minimize an objective function, which represents a measure of performance, cost, profit, or efficiency. Optimization problems often involve complex, multidimensional search spaces with multiple local optima, making it challenging to identify the global optimum. Traditional optimization methods, such as linear programming or gradient-based approaches, may struggle with such complexity, especially in non-linear, non-convex, or discontinuous scenarios[10].

The Genetic Particle Swarm Algorithm (GPSO) is a hybrid approach that combines the strengths of GA and PSO. By integrating the global search capability of GA with the local search efficiency of PSO, GPSO achieves a better balance between exploration and exploitation. This hybrid algorithm leverages the population-based search mechanism of GA to maintain diversity and avoid premature convergence, while utilizing the velocity-update mechanism of PSO to refine solutions and accelerate convergence. As a result, GPSO is particularly effective for solving complex optimization problems with high-dimensional, non-linear, or multi-modal objective functions.

In summary, GPSO represents an advanced optimization technique that enhances the search process by combining the evolutionary principles of GA with the swarm intelligence of PSO. Its ability to efficiently navigate complex search spaces makes it a powerful tool for objective optimization in various fields, including engineering design, resource allocation, and machine learning.

3. Experiments

3.1 Optimization Model

This paper adopts the median selling price of crops as the sales price, as shown in formula (1).

$$A_{j}=\frac{A_j^{(max)}+A_j^{(min)}}{2} \tag{1}$$

Directly assuming the yield as the expected sales volume is not realistic. Therefore, this paper uses the price elasticity coefficient to estimate the expected sales volume. The price elasticity coefficient refers to the ratio of the change in sales volume of a certain commodity to the change in its price, as shown in formula (2).

$$D_j = \frac{n_j - n_j^{'}}{P_j^{max} - P_j^{min}} \tag{2}$$

Based on the price ranges the corresponding price reductions for different crops can be obtained, and combined with the price elasticity coefficient the formula for the sales volume reduction can be derived as formula (3).

$$h_i = e_i \times D_j \tag{3}$$

Combining the sales decline and the elasticity coefficient allows the expected sales volume of different crops to be calculated with the following formula (4).

$$m_j = n_j \times (1 - h_i) \tag{4}$$

Due to the multidimensionality of the variables, the diversity and overlapping of the constraint information, this paper adopts the linear programming method to establish a mathematical model for problem one. In order to facilitate farming operations and field management, each plot planted crop types can not be too much, this paper assumes that the upper limit of a plot planted crop types for N (the text takes N = 4 for solving), so each plot can be divided into N parts of the solution.

A. Decision variables

In this paper, the total amount of j crops grown in season k of year t in block number i is used as the decision variable.

B. Constraints

(1) Planting area constraint: the sum of the planting area of various crops cannot exceed the sum of the area of all planting plots.

$$\sum_{j=1}^{41} x_{jk1} \leq \sum_{i}^{6} I_i \tag{5}$$

(2) Discontinuous recrop planting constraint:

From the title it can be seen that only the wisdom shed is possible to plant the same type of crop in two seasons in a year, so in addition to the constraint that the two adjacent years can not be planted at the same time the same crop, but also constraints on the same type of crop can not be planted in the same two seasons in the same year. The rest of the types of plots can only be planted in a single season each year or two seasons of planting different vegetables so it is only necessary to ensure that the two adjacent years do not continuously re-crop planting.

① Intelligent greenhouse:

$$\begin{gathered} x_{i1t}^{(j)} \times x_{i2t}^{(j)} = 0 \quad t = 0,1,\ldots,7 \quad i \in I_6 \\ x_{(i+1)1k}^{(j)} \times x_{i2t}^{(j)} = 0 \quad t = 0,1,\ldots,6 \quad i \in I_6 \end{gathered} \tag{6}$$

② The rest of the plot types:

$$x_{ikt}^{(j)} \times x_{ik(t+1)}^{(j)} = 0 \quad t = 0,1,\ldots,6 \quad i \notin I_6 \tag{7}$$

(3) Beans planting constraints:

To ensure soil fertility needs to ensure that beans in the same piece of arable land at least once every three years. Set $\mathrm{Count}(x_{ikt}^{(j)})$ for the same piece of land to determine whether the planting of beans function, when the planted crop is beans is the output value of 1; non-legume plants when the output value is 0.

$$\sum_{i=i'}^{i'+2}\sum_{j} count(\mathrm{x}_{\mathrm{ikt}}^{(\mathrm{j})}) \geq 1 \quad t \in \{0,1,\ldots 5\} \tag{8}$$

(4) Planting density constraints:

In order to ensure that crops can grow normally, the planting area of various crops in a single plot should not be too small. However, due to the shed can be used in the area of arable land and the rest of the type of land compared to the difference is too large, so the direct use of the area of different plots to do comparisons is not in line with the reality, so this paper introduced y_{min} for for a single piece of arable land for the minimum use of the area and the total area of the ratio, and this paper assumes that the $y_{min} = \frac{1}{\mathrm{N+1}}$, with a single piece of arable land in the same season, the use of the area of arable land to ensure that it does not exceed 1.

$$\begin{gathered} y_{ikt}^{(j)} \geq y_{min} \\ \sum_{j=1}^{N} y_{ijk}^{(j)} \leq 1 \end{gathered} \tag{9}$$

C. Objective function

The optimal planting scheme should maximize profit, and the profit function of the planting scheme is in two scenarios:

(1) Excess lagging

$$\mathrm{maxW} = \sum_{\mathrm{j}}\sum_{\mathrm{k}}\sum_{\mathrm{t}} \mathrm{A_{jkt}} \min(\mathrm{M_{jkt}}, \mathrm{T_{jkt}}) - \mathrm{C_{jkt}T_{jkt}} \tag{10}$$

(2) The stagnant portion is sold at a 50% discount to the hypothetical 2023 sales price

$$\mathrm{maxW} = \sum_{\mathrm{j}}\sum_{\mathrm{k}}\sum_{\mathrm{t}} \mathrm{A_{jkt}M_{jkt}} - \mathrm{C_{jkt}T_{jkt}} - \frac{\mathrm{A_{jkt}}}{2}\min(\mathrm{T_{jkt}} - \mathrm{M_{jkt}}, 0) \tag{11}$$

D. Model integration

Objective function is:

$$\mathrm{maxW} \tag{12}$$

Constraints are:

$$\begin{cases} \sum_{j=1}^{41} x_{jk1} \leq \sum_{i}^{6} I_i \\ x_{i1t}^{(j)} \times x_{i2t}^{(j)} = 0,\ t = 0,1,\ldots,7 \quad i \in I_6 \\ x_{(i+1)1k}^{(j)} \times x_{i2t}^{(j)} = 0,\ t = 0,1,\ldots,6 \quad i \in I_6 \\ x_{ikt}^{(j)} \times x_{ik(t+1)}^{(j)} = 0,\ t = 0,1,\ldots,6 \quad i \notin I_6 \\ y_{ikt}^{(j)} \geq y_{min} \\ \sum_{j=1}^{N} y_{ijk}^{(j)} \leq 1 \\ \sum_{\mathrm{j}}\sum_{\mathrm{k}}\sum_{\mathrm{t}} \mathrm{N_{ikt}^{(j)}} \leq \mathrm{N_{max}} \\ \sum_{j=\mathrm{J}_1} x_{ikt}^{(j)} = 0,\ i \notin I_4 \\ \sum x_{ikt}^{(j)} = 0,\ i \in I_i,\ i = 1,2,3 \text{ 且 } \mathrm{j} \notin \mathrm{J}_2 \\ \sum x_{i1t}^{(j)} = 0,\ i \in I_4 \text{ 且 } \mathrm{j} \notin \mathrm{J}_3 \\ \sum x_{i2t}^{(j)} = 0,\ i \notin I_4 \text{ 且 } \mathrm{j} \in \mathrm{J}_1 \\ \sum x_{i1t}^{(j)} = 0,\ i \in I_5 \text{ 且 } \mathrm{j} \notin \mathrm{J}_3 \\ \sum x_{i2t}^{(j)} = 0,\ i \notin I_5 \text{ 且 } \mathrm{j} \in \mathrm{J}_4 \\ \sum x_{i1t}^{(j)} \neq 0 \text{ 且 } \sum x_{i2t}^{(j)} \neq 0,\ \mathrm{j} \in \mathrm{J}_3 \end{cases} \tag{13}$$

3.2 GPSO Model

Genetic particle swarm algorithm (GPSO) combines genetic algorithm (GA) and particle swarm optimization algorithm (PSO), comprehensively utilizes the global search of genetic algorithm and the local search ability of particle swarm algorithm, with faster convergence speed, greatly improves the search efficiency of the algorithm, and the adaptability is enhanced, which can be used to solve complex problems. Specifically, it includes three basic operations: genetic operation, particle swarm operation, and information exchange.

(1) Genetic operation: select individuals for reproduction based on fitness, perform crossover operation to generate new generation, and perform random mutation on individuals to increase population diversity.

(2) Particle swarm operation: update the velocity and position of the particles, focus on the individual best (pbest) and global best (gbest), and adjust the particle behavior according to the algorithm rules.

(3) Information exchange: transfer the excellent individual information from the genetic algorithm to the particle swarm algorithm and vice versa. The basic process and its flow chart are as follows:

- At the beginning of the calculation, initialize the chromosomes of the genetic algorithm and the particles of the particle swarm algorithm in the population, and set the required algorithm parameters, such as crossover rate, mutation rate, inertia weight, and acceleration constant.
- Use the objective function to evaluate the fitness of each individual in the population.
- Perform genetic operations
- Perform particle swarm operations
- Exchanging the information of the best individuals, the crossover and mutation operations of the genetic algorithm can be used to guide the search of the particle swarm algorithm.
- Set the termination conditions of the algorithm, such as reaching the maximum number of iterations, finding a satisfactory solution, or the change of fitness is less than a certain threshold.
- Output the optimal solution or the set of optimal solutions.

4. Results and Analysis

Using a genetic particle swarm algorithm to solve the model that

(1) More than part of the stagnation, resulting in waste

This paper draw the genetic particle swarm algorithm fitness curve in Fig. 1.

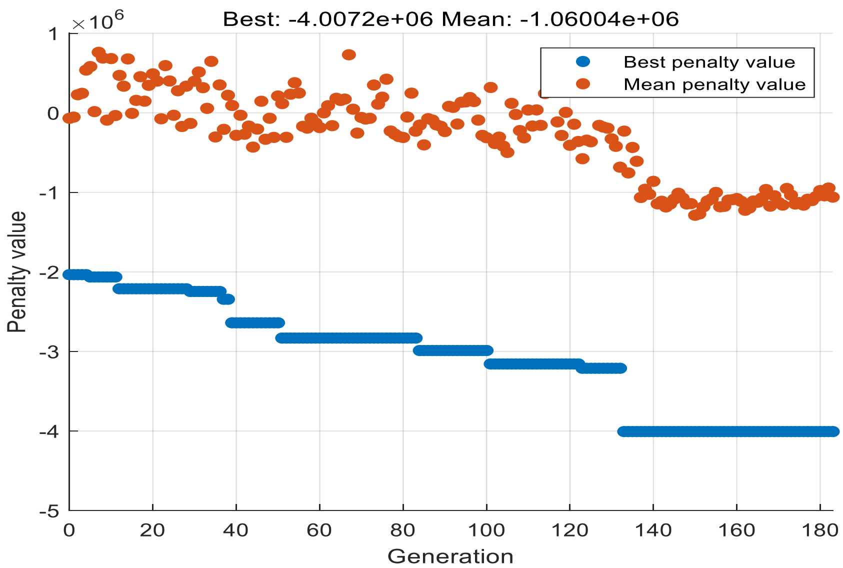

Fig. 1 Case 1 Genetic particle swarm algorithm fitness curve

The optimal planting scheme visualization results are shown in Fig. 2:

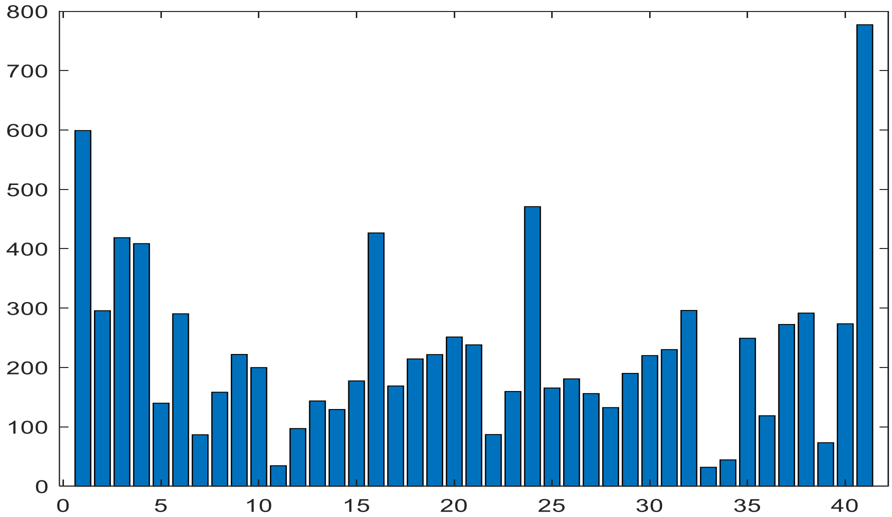

Fig. 2 Situation one planting strategy visualization result

From Figs. 1-2, it can be seen that the planting of grain and vegetable crops is stable and average, the average yield of bean crops is higher, and the yield of fungus varies greatly. The reason is hypothesized as follows: under the condition of overproduction lag waste, the yield is higher than the cost of demand, the planting of higher cost of fungus crops and legume crops selective planting, economic benefits and market demand for high planting more, so the above two different types of yield differences are larger. And grain crops market demand, price stability, in excess of the production of stagnant waste conditions, the market risk of grain crops is low, so the planting type of production is evenly distributed, planting more.

(2) The excess is sold at a price reduction of 50% of the sales price in 2023

Our study draws the fitness curve in Fig. 3.

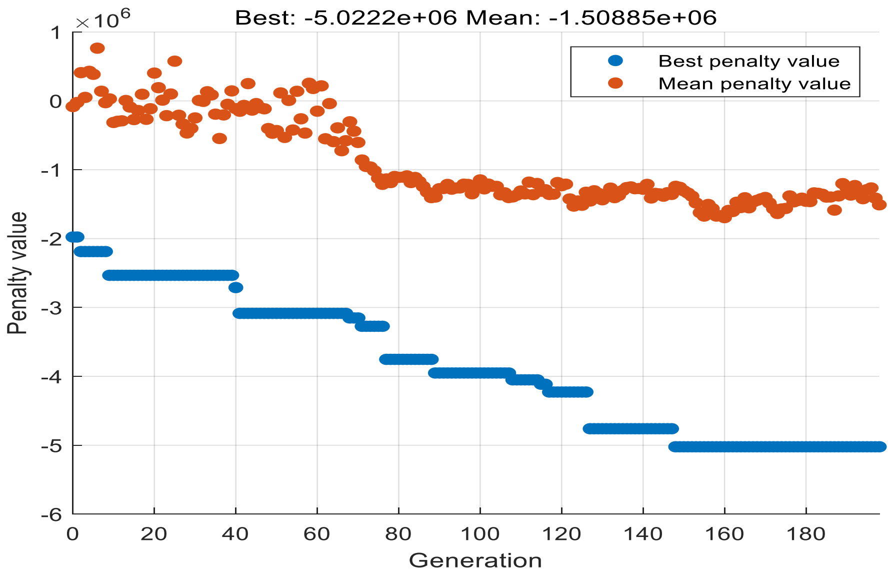

Fig. 3 Case II genetic particle swarm algorithm adaptation curve

Our study draws the distribution of planting scheme in Fig. 4.

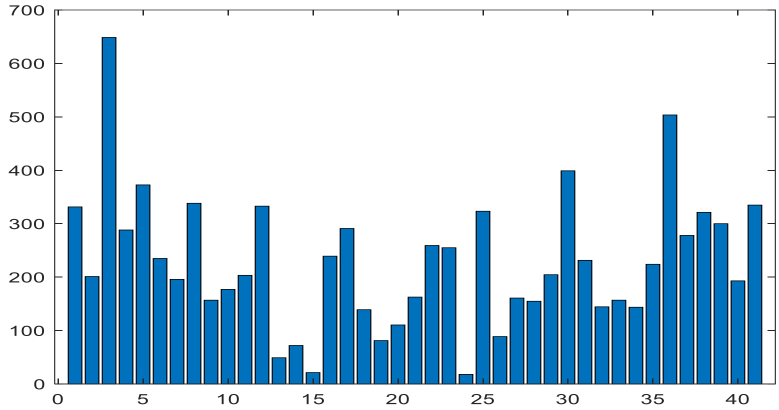

Fig. 4 Visualization of planting strategy for case II

From Figures 3-4, the average yield of legume crops and mushrooms is the highest and generally higher than the yield under the overproduction and waste condition; the average yield of grain crops is about 200 pounds per acre and is lower than the yield under the overproduction and waste condition, and vegetables are about 250 pounds per acre. The reasons are speculated as follows: under the conditions of overproduction and price reduction and sale, mushroom crops and bean crops, even if they are overproduced, their economic benefits are still considerable, so the above two plantings are on the high side, and the yield is higher on average. Grain crops market demand, price stability, but the economic benefits are not as good as vegetables, so the average grain production is low. The reason for the low yields of sweet potatoes, barley, oat, and green peppers is hypothesized to be lower market demand and a smaller audience.

5. Conclusions

This study combines objective optimization with Genetic Particle Swarm Algorithm to plant crops. On the premise that more than part of the stagnant sales, resulting in wastage, the cost of yield overruns is higher, so the economic returns are better when growing crops with stable market conditions such as grains. Under the premise that more than some of them are sold at reduced prices, yield overruns are less costly for crops with higher price elasticity, so the choice is to plant more fungus crops that are economically profitable and have high prices. This reveals us: when the market oversupply, if the crop out of a wide range of ways (such as melons and fruits in addition to freshly sold can also be used for food processing, made of dried fruits and vegetables and fruit juice drinks), and the price is considerable, can be achieved above the overproduction of price reduction in the sale of the situation, then you can planting the appropriate more than a number of. On the contrary, the amount of planting should be appropriately reduced.

6. References

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