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A Multi-Objective Optimization Model for Agricultural Crop Planting Strategies Using Enhanced Genetic Algorithms and Big Data Analysis

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Abstract. The purpose of this paper is to construct an optimization model of crop planting strategy based on improved genetic algorithm. In order to improve the efficiency of agricultural planting and maximize the economic benefits, this paper combines the linear programming model and the multi-matrix improved genetic algorithm (MI-GA), the improved NSGA-II algorithm of orthogonal experimental design, and the multiple nonlinear regression model based on heuristic exploration algorithm to explore the complex relationship between crop sales price, planting cost and yield per mu. Through the comprehensive analysis of planting constraints, market fluctuations and risk assessment of different crops, a more scientific and practical optimal planting scheme was proposed. Experimental results show that the constructed model has good convergence and optimization effect under the condition of multi-parameter change, which provides decision support for agricultural production and helps to realize the sustainable development of rural economy.

Keywords: Crop Planting Strategy; Genetic Algorithm Optimization; Multiple Nonlinear Regression.

1. Introduction

With the progress of science and technology and the development of market economy, agricultural production is facing more and more challenges and opportunities, and the construction of high-standard farmland is an important means to improve the quality of cultivated land and ensure national food security [1]. Improving the planting efficiency and yield of crops is a key goal in agricultural production [2], which is conducive to promoting the sustainable development of rural economy [3]. Under the conditions of market economy, economic factors such as the planting cost, yield per mu and sales price of crops have an important impact on the formulation of planting strategies, and how to reasonably plan and adjust the planting structure of crops to adapt to market changes and resource conditions has become a problem that agricultural producers and decision-makers must face [4].

Agricultural producers need to predict future price trends and sales trends based on market information, and rationally arrange the planting area and planting structure of crops to maximize profits [5]. At the same time, it is also necessary to develop green agriculture and circular agriculture taking into account the growth characteristics of crops, soil conditions, and the sustainability of agricultural production [6]. Therefore, with the development of modern social technology, how to finely monitor the planting of complex crops of different types of farmland, and how to combine phenological information and time series data to effectively identify large-scale crops [7], are the keys to realizing agricultural area survey and crop yield estimation in the field of smart agriculture and rural areas [8].

In addition, how to construct a crop planting recommendation system based on big data technology and provide agricultural producers with data-driven accurate planting suggestions through in-depth analysis of a huge collection of agriculture-related data has a significant role in modern agricultural production [9]. To maximize economic and social benefits, it's crucial to create tailored production strategies using advanced mathematical analysis [10]. This paper introduces the OED-NSGAII algorithm, a heuristic nonlinear regression model, to optimize planting for economic gains.

2. Description of the application method

2.1. Linear programming models

Linear programming models are often used to solve how to maximize or minimize a linear objective function given constraints. The model implementation process is as follows [11]:

2.1.1. Build decision variables.

The planting area of each crop in different seasons of different plots (including greenhouses) is set as a decision-making variable every year, that is, a multi-dimensional variable is set $x_{i,j,s,t}$ to $x_{i,j,s,t}$ represent the $t(t = 2024{,}2025 \cdots 2030)$ area of the first crop planted in the first season i of the first s plot (including greenhouses) j in the year, and the unit is mu. The i numbering order is flat and dry land, terraced fields, hillside land, irrigated land, ordinary greenhouses and smart greenhouses.

Where:

i is Plot type, $i = 1,2, \cdots N$ and $54 \le N$, j is Crop species, $j = 1,2, \cdots M$ and $j = 1,2, \cdots 41$, s is Seasons of the year, $s = 1,2$ and $i = 1,2 \cdots 26$, Only $s = 1, t\ is$ the year, $t = 2024{,}2025 \cdots$

2.1.2. Determine the objective function.

The objectives of this paper are: Maximize total profit:

$$max \sum_{t=2024}^{2030} \sum_{j=1}^{41} (R_{j,t} - C_{j,t}) \tag{1}$$

$$C_{j,t} = C_j \times \sum_{s=1}^{2} \sum_{i=1}^{N} x_{i,j,s,t} \tag{2}$$

Where, the expression $R_{i,t}$ is as follows:

a. More than part of the unsalable, resulting in waste.

Unsalable products cannot be sold for profit, which directly causes waste. Sales revenue is calculated as:

$$R_{j,t} = P_j \times \min(F_{j,s}, \sum_{s=1}^{2} \sum_{i=1}^{N} x_{i,j,s,t} \times Q_j) \tag{3}$$

Where, P_j: The selling price of the j-th crop, the unit is yuan/jin. $F_{j,s}$: Expected sales volume for the j crop in the first quarter s in catties. Q_j: The yield per mu of the j-th crop is in catties.

b. The excess portion will be sold at a reduced price of 50% of the 2023 sales price.

Slow-moving products can be sold for a profit, but their price will be reduced by 50% of the 2023 sales price. Sales revenue is calculated as:

$$R_{j,t} = P_j \times \min(F_{j,s}, \sum_{s=1}^{2} \sum_{i=1}^{N} x_{i,j,s,t} \times Q_j) + 0.5 \times P_j \times (\sum_{s=1}^{2} \sum_{i=1}^{N} x_{i,j,s,t} \times Q_j - F_{j,s})^{+} \tag{4}$$

Where, $(a)^{+} = \max(a, o)$, which means the greater number in 0 and a

2.1.3. Determine the constraints.

a. Constraints on plot planting:

For different plots, only crops suitable for that plot can be planted, and the formula is expressed as: When

$$\tilde{j} \notin Z_i\,,\quad x_{i,\tilde{j},s,t} = 0 \tag{5}$$

b. Crop season constraints:

For plots that can only be planted with a single crop: flat land, terraced land, and hillside land, because the plot is numbered as the first 26 plots, the formula is expressed as:

$$x_{\tilde{i},j,2,t} = 0, \tilde{i} = 1, 2, \cdots 26 \tag{6}$$

For crops that can only be planted in a single season, the constraint formula for not planting in the second season is expressed as: When j is a crop that can only be grown in a single season

$$x_{i,\tilde{j},2,t} = 0 \tag{7}$$

c. Land use constraints:

The planting area of each plot and greenhouse in each season cannot exceed its total area, and the formula is expressed as:

$$\sum_{j=1}^{M} x_{i,j,s,t} \le S_i, \forall i, s, t \tag{8}$$

Where, S_i: The total area of the i-th plot, measured in acres.

d. Constraints that cannot be repeated:

The same crop cannot be planted continuously on the same plot, and the formula for this constraint is expressed as:

$$x_{i,j,s,t} \times x_{i,j,s,t-1} = 0, \forall i, j, s, t \ge 2025 \tag{9}$$

e. Legumes Crop Constraints:

Each plot is required to be planted with pulses at least once in three years, and the constraint formula is expressed as:

$$\sum_{y=0}^{2} \sum_{j \in B_i} \sum_{s=1}^{2} x_{i,j,s,t-y} \ge 0, \forall i, t \ge 2026 \tag{10}$$

f. The planting area should not be too small:

This paper finds that the minimum planting area in 2023 is 0.3 mu, so this paper assumes that the minimum planting area is 0.3 mu, and at the same time, the constraint also ensures the non-negativity of the decision variable, and the constraint is expressed as follows:

$$x_{i,j,s,t} = 0 \ or \ x_{i,j,s,t} \geq 0.3, \forall i, j, s \quad (11)$$

2.1.4. Sensitivity analysis.

Some key parameters in the objective function and constraints have a significant impact on the results, and this parameter is uncertain. The following parameters are considered sensitive:

$d_{j,t}$: The expected sales volume of the j-th crop in the year t, in catties.

$y_{j,t}$: The yield of the j-th crop per mu in the year t, in catties.

$c_{j,t}$: The planting cost of the j-th crop in the year t, in yuan/mu.

$p_{j,t}$: The selling price of the j-th crop in the year t, in yuan/catty.

Parameter perturbation settings:

In this paper, we will perturb sensitive parameters and observe the changes in the optimal solution and the value of the objective function.

(1) Expected sales volume:

For wheat and corn, i.e., the average annual growth rate of expected sales is between 5% and 10%. The range of perturbation variation is expressed as:

$$[d_{j,t} \times 1.05, d_{j,t} \times 1.10] \quad (12)$$

For crops other than wheat and corn, the expected annual sales volume in the future will change $\pm 5\%$ approximately compared to 2023, and the range of disturbance changes is expressed as:

$$[d_{j,t} - 5\%, d_{j,t} + 5\%] \quad (13)$$

(2) Yield per mu:

The yield per mu of crops will vary $\pm 10\%$ from year to year, and the range of disturbance changes is expressed as:

$$[y_{j,t} - 10\%, y_{j,t} + 10\%] \quad (14)$$

(3) Planting cost:

The cost of planting crops increases on average 5% around the same year, assuming that the disturbance range is 1%, then the disturbance range is expressed as:

$$[c_{j,t} \times 1.04, c_{j,t} \times 1.06] \quad (15)$$

(4) Sales price:

The selling price of grain crops is basically stable, and there is no disturbance range.

The average annual increase in the selling price of vegetable crops is about 5%, assuming that the disturbance range is 1%, then the disturbance range is expressed as:

$$[p_{j,t}\times 1.04, p_{j,t}\times 1.06] \quad (16)$$

The selling price of edible mushrooms decreases by about 1% to 5% per year, where the selling price of morel mushrooms decreases by 5% per year, assuming that the perturbation range is 1%, then the perturbation range is expressed as:

For edible mushrooms other than morels:

$$[p_{j,t}\times 0.95, p_{j,t}\times 0.99] \quad (17)$$

For morels:

$$[p_{j,t}\times 0.94, p_{j,t}\times 0.96] \quad (18)$$

2.1.5. Linear programming models that consider correlation and uncertainty.

The linear programming model, which takes into account correlation and uncertainty, is improved only in the objective function:

$$max\sum_{t=2024}^{2030}\sum_{j=1}^{41}((p_{j,t}+\rho_p)\times \min(F_{j,s},\sum_{s=1}^{2}\sum_{i=1}^{N}x_{i,j,s,t}\times y_{j,t})-(c_{j,t}+\rho_c)\times\sum_{s=1}^{2}\sum_{i=1}^{N}x_{i,j,s,t}) \quad (19)$$

Where, ρ_p : correlation adjustment factor for sales prices between crops, ρ_c : correlation adjustment coefficient of planting cost between crops.

2.2. Multi-matrix Improved Genetic Algorithm (MI-GA)

The Multi-Matrix Improved Genetic Algorithm (MI-GA) is an extension and improvement of the traditional Genetic Algorithm (GA), which uses multiple matrices to represent and process problems, so that the algorithm can solve complex optimization problems more effectively.

2.2.1. Decide how you want to encode.

In this paper, the multi-matrix improved genetic algorithm is used to solve the linear programming model, so the output results are expressed as a combination of multiple matrices, and the matrix is constructed based on the representation of crop types and planting plots, and each row in each matrix represents the relevant constraints, and the data is converted into a multi-matrix input form.

2.2.2. Initialize the population.

By randomly generating multiple initial solutions, each solution is represented by a number of matrices, the elements in which represent the values of the variables and the distribution of constraints. In this paper, the empty solution is established by using the year as the span, and then the solution is generated every year based on the planting plot and crop type, and the unfeasible solution is repaired according to the constraints.

2.2.3. Determine the fitness function.

Fitness assessment for each individual, based on the objective function of linear programming, our fitness function is as follows:

$$f(x)=c^T x \quad (20)$$

At the same time, it is also necessary to consider whether the constraints are satisfied, and if they are not met, the punishment will be carried out, which is directly proportional to the degree of violation of the constraints:

$$f_{penalized}(x) = f(x) - \lambda \times Penalty \tag{21}$$

Where, is the λ penalty coefficient, and $Penalty$ is the degree to which the constraint is violated;

2.2.4. Select, cross, and mutate operations.

According to the fitness value, methods such as roulette selection and tournament selection were used to select individuals with higher fitness for mating. Individuals represented by multiple matrices can be hierarchically selected according to different matrix dimensions. Intersecting operations can be improved by intersecting multiple matrices on an element-by-element or column-by-column basis. Rows or columns of different matrices can be randomly combined to generate new child matrices. The mutation operation enhances the diversity of solutions by randomly mutating the elements in the matrix. An element in the matrix can be randomly selected to make a small perturbation or a complete change with a certain probability.

2.2.5. Non-repairable policies.

A total of 5 irreparable strategies were formulated to screen the relevant results generated by the genetic algorithm, so as to further realize the implementation of constraints, and limit under multiple methods to achieve optimization.

(1) Crop planting restrictions on irrigated land

In the fix1 function, for the restriction of planting rice in irrigated land, if rice is planted in the first season, it must be forced to be set to 0 in the second season. If there is a watered plot that cannot be grown in the first season, in some cases, it can lead to the ineffectiveness of the entire planting scheme.

(2) Three-year rotation of pulses

In the fix3 function, for the cultivation of legume crops, it is required that the same beans cannot be planted for three consecutive years. If there is no planting option in a given plot that meets the conditions for crop rotation, this will result in the inability to meet the requirements of crop rotation.

(3) Heavy stubble

In the fix2 function, stubble repair deletes duplicate plantings of the same plot and crop, and if the crop in the planting plan is deleted in a given year, then this can cause some plots to not be able to grow any crops in certain years.

(4) Crop dispersion restrictions

In the fix4 function, the crop dispersion limit requires that each crop cannot be planted more than 5 plots per year. If the number of existing crops reaches the limit, and the newly generated plan cannot be adjusted to meet the eligible combinations, it will create an irreparable situation.

(5) Area restrictions

In the fix5 and fix6 functions, the limits for the minimum and maximum planting area. If the planting area of a plot cannot be adjusted within the given limit, it may result in the planting plan not being met.

(6) Multi-matrix collaborative iteration

In each iteration, the process of "selection-crossover-mutation" is repeated continuously, and individuals with higher fitness are retained. Iterate until a set stopping condition is reached (such as the number of iterations or fitness values as expected).

2.3. Orthogonal design of experiments with improved NSGA-II algorithm (OED-NSGA-II)

OED-NSGA-II blends orthogonal design with NSGA-II for optimized evolutionary parameters, improving efficiency and reducing computation time. It may use NDX to enhance spatial search and mitigate SBX-related issues in traditional NSGA-II.

2.4. Multiple nonlinear regression model based on heuristic exploration algorithm

The multiple nonlinear regression model based on heuristic exploration algorithm combines the global search ability of heuristic algorithm with the prediction ability of nonlinear regression model, aiming to solve complex nonlinear relationship problems.

In this paper, a multivariate nonlinear regression model covering five sub-terms was established to measure the relationship between the expected sales volume of each crop, the sales price and the planting cost.

2.4.1. Model Expressions.

A multiple nonlinear regression model was established with the expected sales volume as the dependent variable y and the sales price and planting cost as the independent variables, which were represented by p and c, respectively, and the model was expressed as:

$$y=\beta_0+\beta_1 p+\beta_2 c+\cdots+\beta_9 p^5+\beta_{10} c^5+\beta_{11}(p\times c)+\cdots+\beta_l(p^m\times c^n)+\varepsilon \tag{22}$$

Where, $\beta_0,\beta_1,\cdots,\beta_l$: regression coefficient to be estimated; ε : random error term; p^m Sum c^n : represents the higher order term of P the sum of independent variables c, and can be combined up to 5 times;

2.4.2. Parameter estimation.

In this paper, the model parameters are estimated using the nonlinear least squares method β_i , to minimize the sum of squares of error:

$$SSE=\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \tag{23}$$

3. Results

3.1. Model solving based on OED-NSGA-II (Orthogonal Design of Experiments Improved NSGA-II Algorithm)

3.1.1. Experimental setup.

In this paper, an orthogonal experiment was designed to determine the different factors and their levels to collect data on the influence of each factor on the objective function (as shown in Table 1), and a total of 112 (7x16) 9x41 matrices were generated for population generation, and the fitness evaluation was carried out for each individual, and the experimental results obtained in the orthogonal experiment were used as the fitness value.

Table 1. Orthogonal test table

Number of experiments	Annual growth rate of wheat and corn sales	Sales volume fluctuated except wheat and corn	Yield per mu	Annual growth rate of cultivation costs	Annual growth rate of vegetable prices	Annual rate of reduction in the price of edible mushrooms (except morels)	The annual rate of decline in the price of morels
1	5%	-5%	-7%	5%	5%	1%	5%
2	6%	-4%	-6%	5%	5%	2%	5%
3	7%	-3%	-5%	5%	5%	3%	5%
4	8%	-2%	-4%	5%	5%	4%	5%
5	9%	-1%	-3%	5%	5%	5%	5%
6	10%	0%	-2%	5%	5%	1%	5%
7	5%	1%	-1%	5%	5%	2%	5%
8	6%	2%	0%	5%	5%	3%	5%
9	7%	3%	1%	5%	5%	4%	5%
10	8%	4%	2%	5%	5%	5%	5%
11	9%	5%	3%	5%	5%	1%	5%
12	10%	-5%	4%	5%	5%	2%	5%
13	5%	-4%	5%	5%	5%	3%	5%
14	6%	-3%	6%	5%	5%	4%	5%
15	7%	-2%	7%	5%	5%	5%	5%
16	8%	-1%	8%	5%	5%	1%	5%

In this paper, the experimental parameters are set as follows (see Table 2 for details).

Table 2.OED-NSGA-II experimental parameters

Hyperparameters	Parameter meaning	numeric value
ITER	The number of iterations	470
PC	Crossover rate	0.7
PM	Rate of variation	0.3
NIND	Population size	30
mode	Mode selection	2

3.1.2. Analysis of results.

Through 470 iterations of operations, it can be seen from the iterative change curve that the optimization degree of the algorithm increases rapidly in the first 30 iterations, and converges to the optimal solution at 470 iterations, indicating that the algorithm has good convergence, and can obtain the highest profit that can be achieved in the case of multi-parameter changes: 3,197,815.54 yuan, and the planting scheme is shown in Table 3 (part).

By using the OED-NSGA-II algorithm, this paper can reasonably obtain the optimal planting plan of the crops in the village from 2024 to 2030 after considering the expected sales volume, mu yield, planting cost and sales price uncertainty of various crops, as well as the potential planting risks, and at the same time, the highest profitability can be obtained at this time.

Table 3. OED-NSGA-II results

name	soybean	Black beans	Red beans	mung bean	Climb the beans	wheat	corn
A1	0	0	0	0	0	0	0
A2	0	0	0	0	0	0	0
A3	0	0	0	0	0	0	0
A4	0	14.4	0	0	0	0	0
A5	0	0	0	0	0	13.6	0
A6	0	0	0	20.34	0	0	11.4
B1	11.99	0	0	12.03	0	0	0
B2	0	0	9.2	9.2	0	0	0
B3	0	0	0	0	0	0	0
B4	0	0	0	0	0	0	0
B5	0	0	0	6.888	0	0	0
B6	0	0	0	0	0	0	0
B7	0	0	0	0	0	0	0
B8	0	0	0	0	0	0	0
B9	0	0	20.35	0	0	0	0
B10	0	8.088	0	0	0	0	0
B11	0	0	12	0	12	0	0
B12	0	0	0	0	0	0	0
B13	0	0	0	0	0	0	0
B14	0	0	0	0	0	11.62	0

3.2. Solving of multiple nonlinear regression model based on heuristic exploration algorithm

3.2.1. Qualitative analysis.

The three variables of expected sales volume, sales price and planting cost were analyzed, a three-dimensional matrix was constructed, and the relationship between the three was observed and analyzed through the three-dimensional matrix, which is detailed in Figure 1, and the related factors were analyzed.

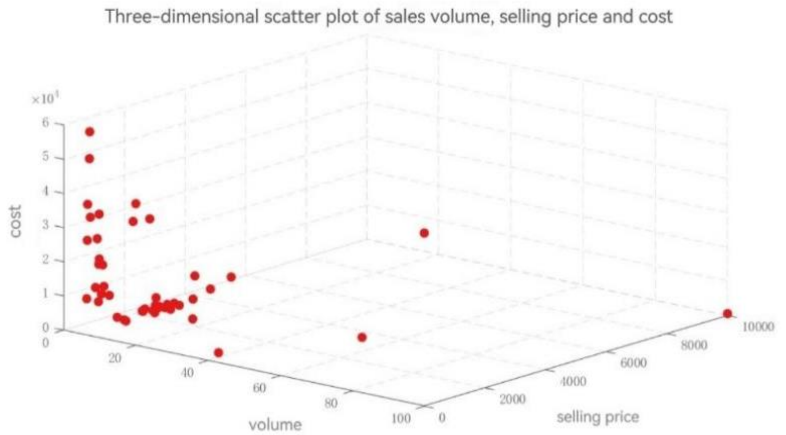

Figure 1. Three-dimensional scatter plot of sales volume, cost and selling price

Figure 1 shows a tight distribution with outliers. This paper will exclude outliers to normalize the data, suggesting a nonlinear relationship. The next section delves into this correlation.

3.2.2. Analysis of results.

In the previous section, we observed that there is a nonlinear relationship between the three, so we construct a 5X5 order matrix to implement a heuristic algorithm starting from (0,0), and take a confidence boundary of 95% to obtain the fitting curve (see Equation 24 and Table 4 for details):

$$
\begin{aligned}
f(x,y) &= p_{00} + p_{10}*x + p_{01}*y + \\
& p_{20}*x^2 + p_{11}*x*y + p_{02}*y^2 + p_{30}*x^3 + \\
& p_{21}*x^2*y + p_{12}*x*y^2 + p_{03}*y^3 + p_{40}*x^4 + p_{31}*x^3*y + \\
& p_{22}*x^2*y^2 + p_{13}*x*y^3 + p_{04}*y^4 + p_{50}*x^5 + p_{41}*x^4*y \\
& + p_{32}*x^3*y^2 + p_{23}*x^2*y^3 + p_{14}*x*y^4 + p_{05}*y^5
\end{aligned} \tag{24}
$$

Where x was normalized to a mean of 11.18 and a standard deviation of 17.74; y was normalized by the mean of 2299 and the standard deviation of 2140;

Here's the Table 4 of coefficient distributions (with a 95% confidence boundary):

Table 4. Coefficient distribution table (95% confidence boundary)

coefficient	numeric value	coefficient	numeric value
p_{00}	-1.556e+04	p_{02}	$-5.74e+04$
p_{10}	$-1.827e+05$	p_{30}	$-2.226e+05$
p_{01}	$-1.607e+05$	p_{21}	$-3.445e+06$
p_{20}	-5.779e+05	p_{12}	-6.945e+05
p_{11}	$-1.415e+06$	p_{03}	$7.699e+04$
p_{40}	9.601e+05	p_{31}	-1.56e+06
p_{22}	-2.131e+06	p_{13}	4.354e+05
p_{04}	-1.068e+04	p_{50}	-2.892e+05
p_{41}	1.297e+06	p_{32}	-5.95e+05
p_{23}	1.971e+05	p_{14}	-2.142e+05
p_{05}	1.696e+04		

The R^2 obtained by the final fitting reached 0.9778, and the adjusted R^2 reached 0.9532, which is an excellent fitting effect and can reflect the quantitative relationship between the three.

Analysis shows a shift in planting: more vegetable varieties and a scattered crop distribution, leading to even planting amounts.

4. Conclusion

This study initiates a crop planting strategy model using linear programming, detailing its construction with planting constraints. It introduces the MI-GA algorithm, explaining its mutation and strategy. Additionally, it examines the refined NSGA-II algorithm's effect on parameter fluctuations, optimizing evolutionary parameters and planting schemes to enhance efficiency and reduce operation time.

By delving into a variety of agricultural models, this study offers the following refined insights and recommendations aimed at enhancing crop cultivation strategies.

By refined NSGA-II with orthogonal design, farmers should optimize resource use for planting, reducing waste and costs, and increasing profits. Crop rotation and intercropping help preserve soil health. The government should encourage organic methods to reduce chemicals, protect the environment, and promote sustainable farming. An insurance system could help farmers mitigate economic risks from disasters.

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