Optimal Planting Strategy for Crops Based on Multi-objective Optimization Algorithm

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Abstract. The sustainable development of rural economy has always been the focus of national and local governments. Under the limited cultivated land resources, the development of organic planting industry according to local conditions can not only improve the utilization rate of land, but also promote the stable growth of rural economy. Based on the data of the American College Students Mathematical Modeling Competition, this paper uses NSGA-II and MOEA/D model to solve the optimal planting scheme and maximum profit of farmers under different sales situations when crop overcapacity in 2024-2030. In addition, this paper also uses Robust NSGA-II algorithm to obtain the optimal planting plan and maximum profit after considering the uncertainty of expected sales volume, yield per mu, planting cost and selling price of crops, which provides theoretical reference for realizing the reasonable allocation of agricultural resources and increasing farmers' income. Finally, this study found that, the best-planting scheme solved by Robust NSGA-II algorithm has higher profit than NSGA-II algorithm and MOEA/D algorithm, while algorithms in uncertain situations are more realistic, indicating that Robust NSGA-II algorithm can guide farmers' crop planting plan.

Keywords: Multi-objective Optimization, Nondominated Sorting Genetic Algorithm II, Multi-objective Evolutionary Algorithm Based on Decomposition.

1. Introduction

Under the limited nature of cultivated land resources, with the growth of the global population, how to improve the efficiency and sustainability of crop planting has become an urgent problem to be solved [1]. As an important part of the real economy, the sustainable development of rural economy has always been the focus of national and local governments. In order to promote the sustainable and healthy development of rural economy, the national and local governments have taken a series of measures, including adjusting the structure and layout of crops and strengthening the field management strategies. Under the limited cultivated land resources, developing organic planting industry according to local conditions can not only improve the land utilization rate, but also promote the stable growth of rural economy [2].

Previous studies have explored the application of multiple optimization algorithms in crop cultivation strategies. For example, Li et al. (2020) developed a model integrating ecological footprint and multi-objective optimization designed to improve the sustainability of farmland use [3]. The model considers multiple dimensions, including resource utilization, economy, society, and environment, by optimizing irrigation water use efficiency, net economic benefits, land resource allocation fairness, and effective farmland allocation scheme, for policy makers to realize the sustainable development of agricultural ecology and greenhouse gas emission [4]. Jain et al. (2021) proposed a hybrid multi-objective optimization algorithm based on the crow search algorithm (CSA) and particle swarm optimization (PSO) for agricultural crop pattern optimization. The study was implemented in Telangana state, India, effectively balancing the contradiction between increasing the net crop income and reducing the use of chemical fertilizers, and providing a new solution to the field of agricultural optimization [5]. Irma Palupi et al. (2022) used genetic algorithms to optimize the crop planting layout in the Cianjur area to maximize land use efficiency and crop yield. By considering the water cost constraints, growth cycle, soil adaptability, and market demand of different crops, they constructed a multi-target optimization model, and successfully found the optimal planting layout scheme [6]. Yang et al. (2020) proposed an algorithm based on the Quality Index Method (SIMM) for solving multi-objective linear fractional programming problems with fuzzy objectives and constraints, and applied it to agricultural planting structure optimization problems. The study takes an irrigation area in Hebei Province, China as an example and considers water-saving crop planning. By optimizing the temporal and spatial layout of crops, the maximum economic, social, and ecological benefits of planting can be achieved under limited water resources [7]. In addition to these studies, recent advancements in multi-objective optimization algorithms have also been applied to address the complexities of agricultural production. For instance, Zhang et al. (2021) reviewed the integration of multi-objective optimization in precision farming to enhance sustainable agricultural development [8]. This highlights the growing importance of leveraging optimization algorithms to address multifaceted challenges in agriculture. Chen et al. (2022) demonstrated the application of a hybrid algorithm for agricultural water management, further emphasizing the potential of multi-objective optimization in resource allocation [9]. These studies collectively underscore the relevance of multi-objective optimization in modern agricultural practices. Moreover, Gómez et al. (2023) explored climate change adaptation in agriculture using a multi-objective optimization approach [10], which is particularly relevant to the dynamic and uncertain environment faced by modern agriculture. Wang et al. (2024) combined machine learning with multi-objective optimization for agricultural production planning [11], showcasing the potential of integrating advanced technologies to enhance decision-making in agriculture.

Despite some progress in existing research, there are still some deficiencies. First, most studies focus on the optimization of a single objective, while actual crop cultivation problems often involve multiple conflicting goals, such as maximizing profits and minimizing environmental impact. Second, existing studies rarely consider the dynamic changes and uncertainty of crop cultivation, which is particularly important in the face of climate change and market demand fluctuations [12]. Moreover, research on substitutability and complementarity among crops is relatively limited, which limits the flexibility and adaptability of planting strategies. Therefore, this study based on the data of the rural area in north China which provided by national college student mathematical modeling competition, and uses a multi-objective optimization algorithm, considering these factors, and proposing a more comprehensive and flexible strategy for optimal planting of crops.

2. The basic fundamental of model

2.1. NSGA-II genetic algorithm

2.1.1.The structure of NSGA-II genetic algorithm

NSGA-II (Non-dominated Sorting Genetic Algorithm II) is an efficient multi-objective optimization algorithm which combines the non-dominated sorting method with genetic algorithm (GA). For each solution, the crowding distance is calculated by finding the distance to the nearest solution along each objective function, and then the crowding distance is used to modify the fitness of each solution. After iterations, we get the optimal solution for the multi-objective problem. The detailed process is shown in Figure 1.

The algorithm consists of three basic steps, which are:

(1) Generate an initial population P_t of size N randomly, and after non-dominated sorting, selection, crossover and mutation, generate the offspring population Q_t, and unite the two populations together to form the population R_t of size $2N$.

(2) Perform a fast non-dominated sorting and calculate the crowding degree of individuals in each non-dominated layer, and select suitable individuals to form a new parent population P_{t+1}.

(3) Generate a new offspring population Q_{t+1} through the basic operations of genetic algorithm, merge P_{t+1} with Q_{t+1} to form a new population R_t and repeat the above operations until the conditions of the end of the program are met.

The algorithm also needs to be coded to achieve fast non-dominated sorting of populations and congestion distance calculation. The specific algorithm steps are shown in Figure 1:

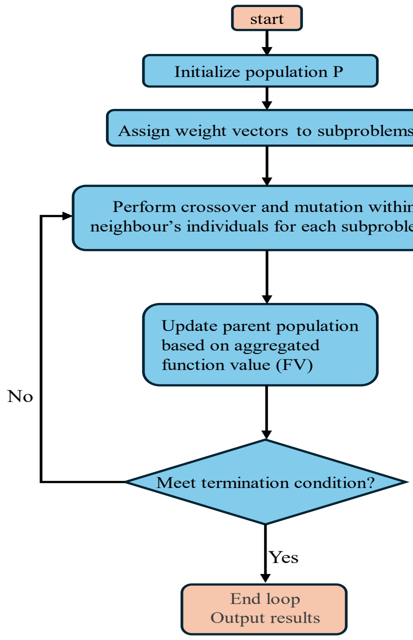

Figure 1. NSGA-II algorithm flow.

2.1.2. The process of determining the non-dominant layer and congestion levels

By analyzing the problem, we establish two objective functions, one is to maximize the total return and the other is to minimize the crop dispersion. The objective functions are expressed as follows:

$$Maximise\ \ f_1 = \sum_i (\min(\sum_j w_i \times q_{ij}, z_i) \times p_i - \sum_j c_{ij} \times q_{ij}) \tag{1}$$

$$minimise\ \ f_2 = \sum_i \sum_j \alpha_{ij} \tag{2}$$

Where f_1 denotes the value of total return, z_i is the expected sales quantity, $\sum_j w_i \times q_{ij}$ is the total production, p_1 is the sales unit price, c_{ij} is the cost of cultivation, and q_{ij} is the cultivated area ,f_2 denotes the degree of crop dispersion, α_{ij} is 0-1 indicator variable.

Non-dominated sorting divides the population into fronts by filtering non-dominated individuals layer by layer. In the target space, an individual x dominates an individual denoted as $x < y$, if and only if the following conditions are satisfied:

$$\begin{cases} \forall m \epsilon \{1,2\}, & f_m(x) \le f_m(y). \\ \exists m' \in \{1,2\}, f_{m'}(x) < f_{m'}(y). \end{cases} \tag{3}$$

The delineation of the non-dominated layer follows the following three steps:

(1) Let n_x=0 $S_x = \emptyset$. Where n_x records the number of individuals dominating x and S_x stores all individuals dominated by x.

(2) Calculate the dominance relationship:

$$\begin{cases} S_x = S_x \cup \{y\}, if x < y. \\ n_x = n_x + 1, if y < x. \end{cases} \tag{4}$$

(3) Stratification is performed. All individuals satisfying $n_x = 0$ are grouped into the Front 1, after which the remaining individuals are recursively processed until all individuals are stratified.

The core of the crowding degree is a measure of the sparsity of the distribution of individuals in the same non-dominated layer. If the currently processed non-dominated layer is the k-th layer, the crowding degree $CD(i)$ of individual i is defined as:

$$CD(i) = \sum_{m=1}^{2}\left[\frac{f_m(i+1) - f_m(i-1)}{f_m^{max} - f_m^{min}}\right] \tag{5}$$

If individual i is an endpoint of the current objective function ordering, then its crowding is assigned an extremely large value $CD(i) = +\infty$.

Ma et al. (2023) reported on the application of this algorithm in real life, which includes resource optimization issues for various types of natural resources [7]. Therefore, for the optimal planting strategy problem of crops, we also employ the NSGA-II model to maximize profits while maximizing the compatibility of land and crops.

2.2. MOEA/D algorithm

2.2.1. The structure of MOEA/D algorithm

MOEA/D (Multi-Objective Evolutionary Algorithm Based on Decomposition) algorithm is a decomposition-based multi-objective optimization algorithm. A MOEA/D with global and local cooperative optimization can solved complicated bi-objective optimization problems [12]. The idea of this algorithm is to decompose a multi-objective problem into N sub-objective problems, first determine one solution for each sub-problem in the neighborhood to form a solution set, and then iteratively optimize the set of solutions continuously to finally arrive at the Pareto optimal solution set.

At the same time, this paper should pay attention to the following points:

(1) The subproblems are solved simultaneously by evolving the solutions in the population P.

(2) At each iteration, the population consists of the optimal solutions found so far for each of the subproblems.

(3) The 'neighborhoods' between the subproblems is determined by the Euclidean distances between the weight vectors.

(4) The optimal solutions of two neighboring subproblems should be very close to each other; each subproblem is optimized using the relevant information of its neighboring subproblems.

2.2.2. The determination of single objective function and parameters

In the problem of investigating the optimal planting strategy for crops, we decompose the multi-objective problem R_2 into 4 single-objective sub-problems, and for each sub-problem, list the corresponding objective functions and assign weight vectors.

Weight vectors $\lambda = (\lambda_1, \lambda_2, \ldots, \lambda_m)^T$, which satisfies:

$$\sum\nolimits_{i=1}^{m} \lambda_i = 1 \tag{6}$$

Let each single objective function be$f_I(x)$, which satisfies:

$$minimise\ \ R_2(x) = \sum_{i=1}^{m} \lambda_i f_i\,(x) \tag{7}$$

Where multi-objective function R_2 is:

$$R_2 = \sum_i (min\,(P_i, z_i) \times p_i + max\,(0, P_i - z_i) \times p_i \times r - \sum_i c_{ij} \times q_{ij}) \tag{8}$$

The MOEA/D algorithm can effectively take into account the effect of the price reduction treatment on the total return in the problem. The Pareto frontier solution is then continuously updated through iterations until the termination condition is satisfied, ultimately finding a set of optimal solutions that trade-off between revenue maximization and price reduction treatment.

3. Results

3.1. Results of NSGA-II and MOEA/D Model

In the constraints of the combination of 50% of the selling price of the crops in three years, and we need to be them in the corresponding plots, using the NSGA-II and MOEA/D planning algorithms, to solve the optimal planting scheme for the rural crops from 2024 to 2030, including the number of acres planted in each plot and the expected maximum profit of the optimal scheme.

For the case of unsalable over-some crops, the optimal profit calculated by NSGA-II algorithm is RMB 45739380 yuan, and for the excess crop is sold at 50% of the sales price in 2023, the optimal profit obtained by MOEA / D algorithm is RMB 47855508 yuan.

At the same time, in order to more briefly compare the crop planting conditions of the two best scenarios, we selected the planting area of 15 crops in the first 26 plots before 2024 to directly reflect the differences between the two scenarios. The final results are shown in Figure 2 and Figure 3.

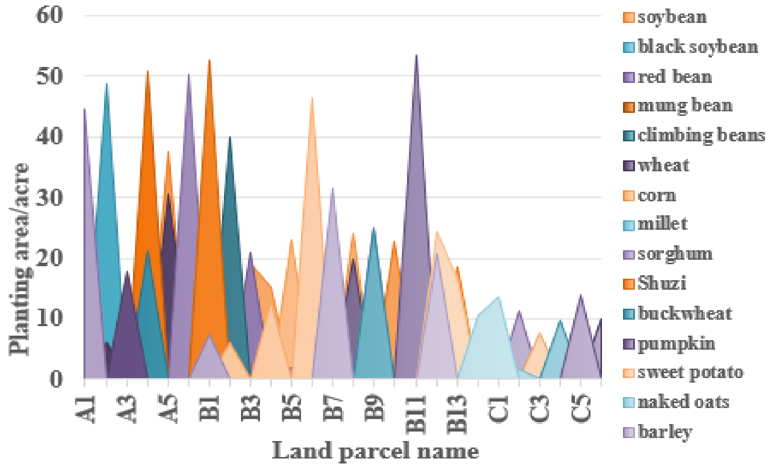

Figure 2. Results plot of the NSGA-II algorithm.

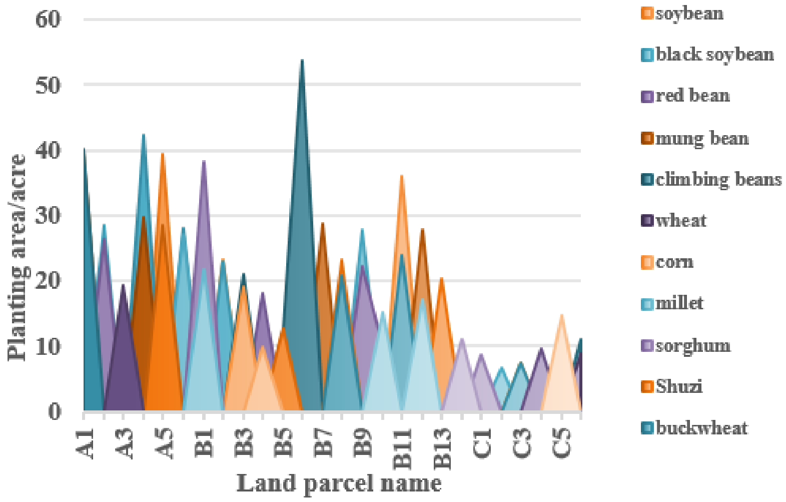

Figure 3. Results plots of the MOEA/D algorithm.

It can be found from the figure that unsalable crops or sale at a price of 50% of the 2023 sale price has a significant impact on the distribution of crops on the different plots, or a higher profit in the second case.

3.2. Results of Robust NSGA-II Model

More deeply, we consider the uncertainty of expected crop sales volume, yield per mu, planting cost and selling price, and the maximum profit solved by using Robust NSGA-II model is 48009405 yuan.

For the convenience of display, we selected the planting area of 15 crops in the first 26 plots before 2024 for drawing, and the results are shown in Figure 4.

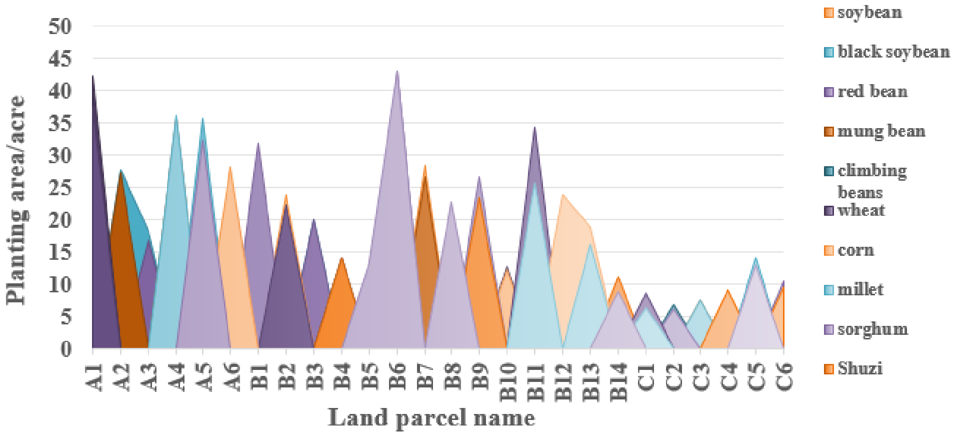

Figure 4. Robust NSGA-II algorithm results.

By comparing the optimal profit bet/ween NSGA-II - MOEA/D model and robust NSGA-II model, we can find that the profit becomes higher after considering the uncertainty of expected sales volume, yield per mu, planting cost and selling price, indicating that such uncertainty can bring opportunities and increase farmers' income. By comparing the crop distribution in NSGA-II - MOEA/D model and robust NSGA-II model, the optimal crop scheme changes greatly after considering the uncertainty.

4. Conclusions and Outlooks

Based on the multi-objective optimization algorithm, this paper studies the crop planting strategy in a mountainous area of North China. First, we established a dual-target optimization model to maximize revenue and minimize the dispersion of crops. We used NSGA-II algorithm and MOEA / D algorithm to solve the situation of unsalable crops and reduced sales respectively, and effectively improved the total profit. Next, we further considered the uncertainty of expected sales volume, per-mu yield, planting cost and selling price, and adopted the Robust NSGA-II algorithm to realize the optimal planting scheme under uncertain conditions by simulating future scenarios. This paper not only provides scientific decision support for rural crop planting, but also significantly improves the efficiency of land use and agricultural economic benefits. This method can be extended to other agricultural fields, such as animal husbandry and aquaculture, to provide a strong guarantee for the sustainable development of agricultural production.

Although the model presented in this paper has achieved remarkable results in solving the problem of crop planting strategies, there are still some deficiencies. Some constraints are difficult to quantify accurately, leading to some bias in the model in practical application. Moreover, some of the assumptions and derivations are too idealized to adequately consider the complexity of realistic situations. Future studies can further refine the constraints to introduce more practical data and improve the accuracy and utility of the model.

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