Research on Crop Planting Scheme Based on PSO-BP Neural Network

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Abstract. This study explores agricultural optimization through two main questions. First, a PSO-BP neural network model was used to derive an optimal planting strategy for profit maximization and cost minimization. The model incorporated yield gap, planting area, and planting practices constraints, resulting in stable, low errors, with a maximum profit of 3,561,194.9 yuan in 2030. For the second question, an optimization model was developed considering expected sales, crop yield, planting cost, sales price, and non-negativity constraints. The model was solved using the simulated annealing algorithm, achieving stability after 35 iterations. The maximum profit reached 4,985,602.86 yuan in 2030, with a minimum of 3,913,304.33 yuan in 2023. This study provides insights into optimizing agricultural production for improved profitability.

Keywords: PSO-BP neural network, optimization model, simulated annealing algorithm.

1. Introduction

Crop selection plays a crucial role in agricultural productivity, especially given the scarcity of arable land and variations in soil nutrients. As a fundamental necessity for human survival, crops significantly impact many aspects of human life. However, the challenges of limited resources and diverse environmental conditions necessitate selecting the most suitable crops and planting strategies to maximize resource efficiency and mitigate the impacts of uncertainties on agricultural yields. Previous studies have highlighted the importance of efficient crop selection to optimize resource use, enhance resilience to environmental changes, and improve overall productivity.

For instance, studies have focused on identifying suitable crops based on soil characteristics and climate conditions to achieve sustainable agricultural development [1]. Resource allocation optimization techniques such as crop rotation, intercropping, and conservation practices have been suggested to maintain soil health and improve yields [2] The use of machine learning models, including neural networks, for predicting optimal crop choices and planting schemes has also gained attention for its ability to manage complexity and uncertainties in agriculture [3-4]. Moreover, optimization algorithms like PSO and genetic algorithms have proven effective for devising cost-efficient crop selection and planting plans [5].

Some studies have also emphasized the role of decision support systems (DSS) in guiding farmers towards optimal crop selection, considering the variability in input resources and market conditions [6]. With an increasing focus on sustainable practices, studies have pointed to the integration of environmental impact assessments in crop selection strategies to ensure long-term sustainability [7]. Addressing uncertainties, particularly those posed by climate change, has led to research focusing on resilient crop planning techniques to secure food supply [8]. Advances in artificial intelligence (AI) and big data analytics have further facilitated precision agriculture, allowing for data-driven crop management decisions [9].

In conclusion, effective crop selection and planting strategies are key to addressing the challenges of limited arable land, resource scarcity, and environmental variability. Integrating advanced modeling techniques, decision support systems, and sustainable practices is critical for improving agricultural productivity and ensuring food security.

2. Methodology

2.1. Construction of multi-objective optimization model

In this paper, a linear programming model is established with the aim of minimizing crop planting cost and maximizing sales profit. Combining the existing information and assumptions of the topic, the objective function is:

$$max \sum_{t=2023}^{2030} \sum_{i=1}^{n} I_t - c_{ijtc} q_{ijt} \tag{1}$$

$$min \sum_{t=2023}^{2030} \sum_{i=1}^{n} c_{ijtc} q_{ijt} \tag{2}$$

Where, I_t represents the total profit obtained from the sale of agricultural products during the period t; c_{ijtc} represents the planting cost of product plots in the broad category in the period; q_{ijt} represents the total production of the product in the category in the period.

The linear programming model needs to satisfy the following constraints:

(1) Output gap constraint: When there is a gap between the output and sales volume of agricultural products, there are two sales forms of agricultural products: (1) the gap part is unsalable; (2) The gap part is sold at 50% of the price. The constraint equation is as follows:

$$I_t = \begin{cases} p_{ijtc} q_{ijt} & condition 1 \\ p_{ijtc} q_{ijt} + 0.5\, p_{ijct} \left(d_{ijt} - q_{ijt} \right) & conditional\ 2 \end{cases} \tag{3}$$

Where, p_{ijtc} represents the sales price of the products in the major categories in the land parcel during the period; d_{ijt} represents the expected sales volume of the product in the category in the period.

(2) Planting area constraint: Since the planting process of vegetables needs to occupy part of the greenhouse area, the planting area of vegetables should not be too small according to the constraints given in the title. Based on this, the planting area constraint of vegetables is given. At the same time, considering the uncertainty of the area in the planting process of vegetables, the interval estimation is carried out by testing under the condition that the data amount is small:

$$Land_c \geq \sum_{i=1}^{n} s_{ijtc} \tag{4}$$

$$s_{ijtc} \in (\overline{S_J} - \frac{\sigma_j}{\sqrt{n}} t_{\frac{\alpha}{2}}, \overline{S_J} + \frac{\sigma_j}{\sqrt{n}} t_{\frac{\alpha}{2}}) \tag{5}$$

$$\sum_{c=1}^{k} s_{ijtc} = s_{ijt} \tag{6}$$

Where, s_{ijtc} represents the planting area of the product in the category in the phase plot; $Land_c$ indicates the area of the plot; $\overline{S_J}$ represents the variance of planted area in the major crop categories.

Constraints on planting laws: According to the information given by the title, the same crop cannot be continuously planted in the same plot, and legumes must be planted once in each land within three years: Constraints are as follows:

$$q_{ijt} + q_{ij(t+1)} = \max\{q_{ijt}, q_{ij(t+1)}\} \tag{7}$$

$$\sum_{t=T}^{T+4} s_{ijtc} > s_{ijmc} \quad m \in [T, T+4] \tag{8}$$

$$j \in \{lsd, ls\ scd, sc\ syj\} \tag{9}$$

In the formula, it respectively represents grain (beans), grain, vegetables (beans), vegetables and edible fungi. In summary, the linear programming model is as follows:

$$Condition\ 1\begin{cases} max\sum_{t=2023}^{2030}\sum_{i=1}^{n} I_t - c_{ijt}q_{ijt} \\ min\sum_{t=2023}^{2030}\sum_{i=1}^{n} c_{ijtc}q_{ijt} \\ I_t = \ p_{ijtc}q_{ijt} \\ Land_c \geq \sum_{i=1}^{n} s_{ijtc} \\ s_{ijtc} \in (\overline{S_J} - \frac{\sigma_j}{\sqrt{n}} t_{\frac{\alpha}{2}}, \overline{S_J} + \frac{\sigma_j}{\sqrt{n}} t_{\frac{\alpha}{2}}) \\ \sum_{c=1}^{k} s_{ijtc} = s_{ijt} \\ q_{ijt} + q_{ij(t+1)} = \max\{q_{ijt}, q_{ij(t+1)}\} \\ \sum_{t=T}^{T+4} s_{ijtc} > s_{ijmc} \quad m \in [T, T+4] \\ j \in \{lsd, ls\ scd, sc\ syj\} \\ s_{ijtc}, c_{ijtc}, q_{ijt},\ p_{ijtc} \geq 0 \end{cases} \tag{10}$$

$$Condition\ 2\begin{cases} max\sum_{t=2023}^{2030}\sum_{i=1}^{n} I_t - c_{ijtc}q_{ijt} \\ min\sum_{t=2023}^{2030}\sum_{i=1}^{n} c_{ijtc}q_{ijt} \\ I_t = \ p_{ijtc}q_{ijt} + 0.5\, p_{ijt}\left(d_{ijt} - q_{ijt}\right) \\ Land_c \geq \sum_{i=1}^{n} s_{ijtc} \\ s_{ijtc} \in (\overline{S_J} - \frac{\sigma_j}{\sqrt{n}} t_{\frac{\alpha}{2}}, \overline{S_J} + \frac{\sigma_j}{\sqrt{n}} t_{\frac{\alpha}{2}}) \\ \sum_{c=1}^{k} s_{ijtc} = s_{ijt} \\ q_{ijt} + q_{ij(t+1)} = \max\{q_{ijt}, q_{ij(t+1)}\} \\ \sum_{t=T}^{T+4} s_{ijtc} > s_{ijmc} \quad m \in [T, T+4] \\ j \in \{lsd, ls\ scd, sc\ syj\} \\ s_{ijtc}, c_{ijtc}, q_{ijt},\ p_{ijt} \geq 0 \end{cases} \tag{11}$$

2.2. PSO-BP neural network

Particle swarm optimization (PSO) is a random search algorithm based on group cooperation established by simulating bird predation behavior. We assume that every optimization problem in the algorithm is a predator in space, and all particles have a fitness value, search direction and search distance. The paper assumes that the position of every particle in space is $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})^T$, and the velocity vector of every particle is $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})^T$, because we give the displacement function in space:

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{12}$$

$$v_{id}^{k+1} = v_{id}^{k} + c_1 r_1^k\left(pbest_{id}^k - x_{id}^k\right) + c_2 r_2^k\left(gbest_d^k - x_{id}^k\right) \tag{13}$$

BP neural network is a kind of artificial neural network, through the signal backpropagation constantly adjust the network layer weight and threshold, so that its output value is constantly approaching the expected output. Generally, the neural network consists of three parts: input layer, hidden layer and output layer. The neurons in different layers are fully connected, and the input of neurons in the layer comes from the output of the neural institute in the previous layer. The neural network structure diagram is as shown in Figure 1:

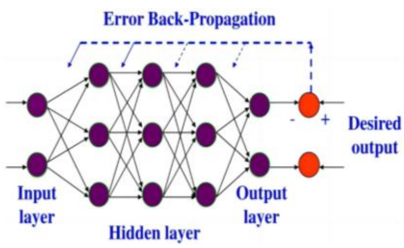

Figure 1. Neural network structure diagram

The neuronal input is as follows:

$$y_j = f(\sum_{i=1}^{n} w_{ij} PRofit_t + b_j) \tag{14}$$

Where, y_j represents the output of neurons; RD_i represents input from neurons; $Profit_t$ represents output data for the period. At the same time, on the original basis and with reference to previous studies, inertia weights were introduced to optimize the model:

$$\omega_i = \omega_{max} - \frac{\omega_{max} - \omega_{min}}{H} z \tag{15}$$

3. RESULTS

3.1. Calculation results of PSO-BP neural network

Through MATLAB software programming, the data of 2023 was brought in to obtain the optimal planting strategy of 2024. The error iteration graphs in two cases are shown in Figure 2:

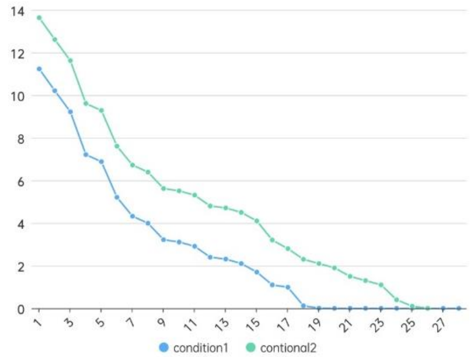

Figure 2. PSO-BP neural network error iteration method

Through Figure 2, we find that the error of the neural network model reaches 0 after 19 and 27 iterations respectively in case 1 and case 2, and the error of the model is small.

Through calculation, the annual profits under the two conditions are obtained, and the results are shown in Figure 3:

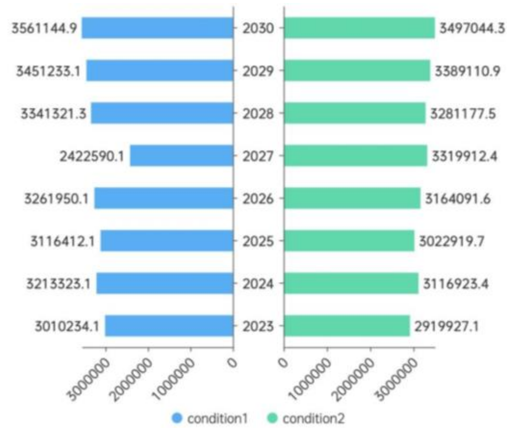

Figure 3. Profit distribution diagram

It is found in Figure 3 that the profit in both cases fluctuates around 300,000 yuan, with the maximum reaching 3,561,194.9 yuan in 2030. A maximum of 34,970,44.3 yuan by 2030;

4. Conclusion

In conclusion, the study utilized PSO-BP neural network and simulated annealing algorithms to determine optimal planting strategies and maximize agricultural profitability from 2023 to 2030. The analysis showed that crop planting areas were relatively stable, with low variability across different crop types. Using PSO-BP neural network modeling, the optimal planting strategy in 2024 indicated minimal error, and the annual profit under two different scenarios demonstrated consistent fluctuation around 300,000 yuan, with a peak in 2030 reaching 3,561,194.9 yuan. Additionally, simulated annealing optimization provided further insights, achieving stability after 35 iterations, and projected significant profit growth with a maximum of 4,985,602.86 yuan in 2030. The results highlight the potential of combining machine learning techniques and optimization algorithms to develop effective, sustainable planting strategies, ensuring enhanced agricultural profitability and stable crop output over time.

References

[1] Gao, Y., Li, M., & Chen, H. (2023). Precision agriculture: AI and big data in crop management. Agricultural Systems, 207, 103496.

[2] Jat, R. A., Wani, S. P., & Sahrawat, K. L. (2020). Conservation agriculture in rainfed systems. Journal of Soil and Water Conservation, 75 (5), 562-570.

[3] Kumar, S., & Shukla, S. (2020). Optimization techniques for cost-effective crop selection. Agricultural Research, 9 (4), 432-440.

[4] Li, X., Zhang, Y., & Li, Z. (2022). Machine learning in optimal crop selection and yield prediction. Computers and Electronics in Agriculture, 198, 107002.

[5] Mishra, R., Verma, P., & Kumar, S. (2021). Decision support systems for crop selection. Computers and Electronics in Agriculture, 186, 106234.

[6] Patel, V., Singh, R., & Sharma, P. (2021). Neural networks for agricultural decision-making. Expert Systems with Applications, 168, 114423.

[7] Singh, A., & Singh, M. (2019). Sustainable crop selection strategies. Journal of Environmental Management, 248, 109239.

[8] Wang, H., & Liu, Q. (2022). Climate resilience in crop planning. Climate Risk Management, 35, 100416.

[9] Zhao, J., Chen, Y., & Gao, Z. (2021). Environmental impact assessments in agriculture. Sustainable Agriculture Reviews, 50, 267-284.