Research on Planting Strategy Based on Game Theory Hybrid Particle Model

Yuqin Qiu *, Ning Zhang and Chungui He
School of Statistics, Beijing Normal University, Beijing, China
* Corresponding Author Email: yukihahaya@163.com

Abstract. Hybrid particle swarm optimization (PSS) is an intelligent optimization method widely used in machine learning. In this paper, we combine evolutionary game theory and particle swarm optimization and apply them to the optimization of farm planting strategies. Firstly, a linear regression model was established by accurately modeling the output, sales volume and other relevant indicators of agricultural products. Then, by using the powerful global search ability of game theory and hybrid particle swarm optimization to solve the optimal solution under constraints. Subsequently, the Monte Carlo method is introduced to incorporate factors such as climate and geographic location into the model, which further improves the accuracy of the prediction. This study not only successfully applies game theory and hybrid particle swarm optimization to the optimization of farm planting strategy, which has high practical value, but also provides a useful reference for similar multi-dimensional programming problems.

Keywords: Game-theoretic mixed-particle models; Game theory; Optimal planting schemes.

1. Introduction

In the field of machine learning, the research and application of intelligent optimization methods continue to develop, among which Hybrid Particle Swarm Optimization (HPSO) has attracted extensive attention due to its superior global search ability. The purpose of this paper is to explore the potential of combining Evolutionary Game Theory (EGT) with hybrid particle swarm optimization and apply this innovative model to the optimization of planting strategies on actual farms. In this paper, an accurate linear regression model is established to quantitatively describe the yield, sales volume, and related indicators of agricultural products. This model provides the basic data and prediction basis for the subsequent optimization process. By introducing game theory and hybrid particle swarm optimization, the global optimal solution under modified constraints and objective functions can be obtained. Then, this paper further introduces factors such as climate and geographical location through the Monte Carlo method, to improve the scientific and effective decision-making. The innovation of this paper is to combine the strategy optimization ability of evolutionary game theory with the global search ability of particle swarm optimization algorithm, which provides a novel idea for solving optimization problems in practical applications.

2. Data Collection and Pre-processing

2.1. Data Collection

In order to explore the application of game theory hybrid particle model in planting strategy, this paper selects a farm in Huabei area as the research object. Through in-depth analysis of the problem, it is concluded that there is the most important relationship between mu yield, planting cost, market sales, sales price and other factors and planting profit. Therefore, this paper first collects and collects the corresponding data of yield per mu, planting cost, average sales unit price, and expected sales volume of each crop in North China.

2.2. Data Preprocessing

After integrating the crop data, it is found that there are some differences in the yield per mu, planting cost and sales unit price of crops in different plot types. Considering that the mean value can reduce the random error, improve the representativeness, and reflect the central trend of the data, in order to facilitate the subsequent modeling to solve the problem, the data pairs of crop yield, planting cost and sales unit price are averaged to solve the non-consistency of crop data on different plots.

2.3. Other Data Analysis

During the field investigation, we found that the farm has a total of 1,201 acres of open cultivated land, which is divided into 34 plots of different sizes, including four types: flat and dry land, terraced land, hillside land and irrigated land. Flat and arid land, terraced fields and hillside land are suitable for planting one season of grain crops per year; Watered land is suitable for planting one crop of rice or two crops of vegetables every year. The farm has 16 ordinary greenhouses and 4 smart greenhouses, each with a cultivated area of 0.6 acres. Ordinary greenhouses are suitable for planting one season of vegetables and vegetables and one season of edible fungi every year, and smart greenhouses are suitable for planting two seasons of vegetables per year. Different crops can be planted in the same plot (including greenhouses) each season. At the same time, this paper learned that according to the growth law of crops, each crop should not be continuously planted in the same plot (including greenhouses), otherwise the yield will be reduced. Because the soil containing the legume crop rhizome is conducive to the growth of other crops, the planting strategy is to plant the legume crop at least once in three years on all land in each plot starting in 2023. At the same time, the planting plan should also consider the convenience of cultivation and field management, for example: the planting area of each crop should not be too scattered each season, the area of each crop planted in a single plot should not be too small.

3. Crop Sales Forecasting Model

3.1. Correlation Analysis

Firstly, the Spearman correlation analysis between the sales volume and the sales price of vegetables in North China from 2002 to 2014 is carried out, and the formula is as follows:

The Spearman correlation coefficient is:

$$r_s = 1 - \frac{6\sum_{i=1}^{n} d^2}{n(n^2-1)} \tag{1}$$

Where n means there are n pairs of data points; x_i, y_i is the rank of the X, Y variable ith Observation.

Table 1. Spearman correlation coefficient matrix for grains.

	foodsale	foodproduce
foodsale	$1(0.000^{***})$	$0.917(0.001^{***})$
foodproduce	$0.917(0.001^{***})$	$1(0.000^{***})$
Note: *Represents the significance level of respectively$***,**$ $,1\%, 5\%, 10\%$		

$\sum_{i=1} d^2$ Is the sum of the squares of the grade difference$(x_i - y_i)$, and n is the number of observations. Through the Spearman correlation analysis of SPSS, the correlation between vegetable yield and its sales price and sales volume in North China was obtained [1-3], and the correlation between grain sales volume and yield was obtained, and a heat map was drawn. Here are the results shown in Table 1 and Fig. 1.

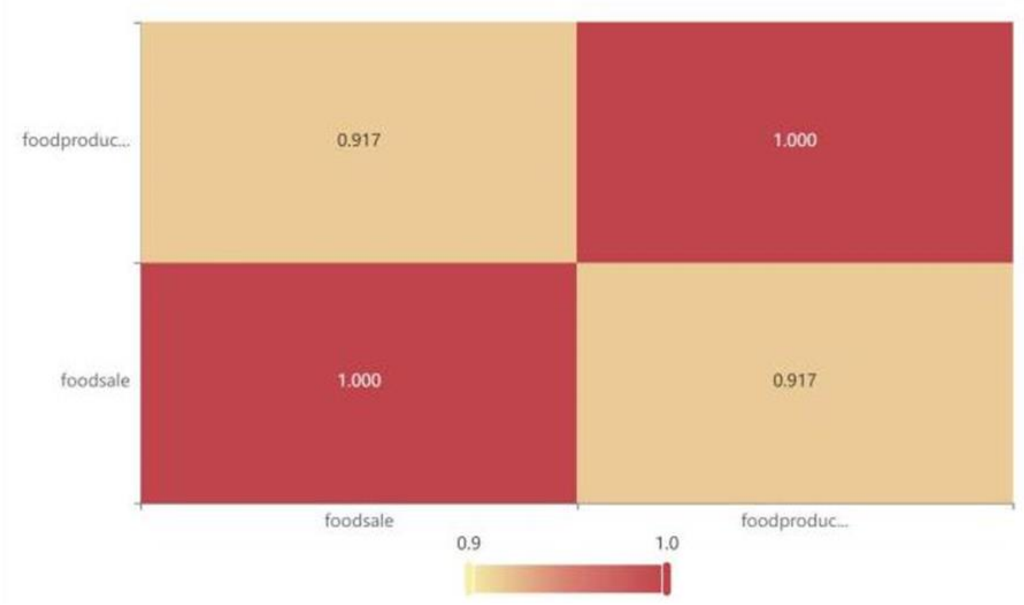

Fig 1. Heat map of grain sales and production.

It was observed that the Spearman correlation coefficients between vegetable sales volume and yield and sales price were -0.367 and 0.317, and the Spearman correlation coefficient between yield and sales volume was -0.267, both showing a small correlation. The correlation coefficient between grain sales volume and yield reached 0.917, which was highly correlated.

3.2. Model Construction

3.2.1. Data preprocessing

First, the standardization of the sales volume and output of agricultural products can effectively eliminate the influence of different units or dimensions on the analysis results, so that the data of different characteristics can be compared and processed on the same scale.

Then, denormalization is carried out, that is, the normalized data is restored to the actual value. At this point, it is assumed that the mean of the production and sales of agricultural products in 2023 is the same as the standard deviation. The formula for denormalization is:

$$x = z \times \sigma + \mu \tag{2}$$

Where x is the value after denormalization and z is the value after normalization, σ is the standard deviation and μ is the mean. With de-normalization, the normalized data can be restored to its original scale for specific practical application or further analysis.

3.2.2. Regression analysis model

Regression analysis models can be used to discover and quantify relationships between variables, and are widely used in prediction, causal analysis, decision support, anomaly detection, and other fields.

It can be found that there is a strong linear relationship between the two. Therefore, the total grain sales in North China can be used as the response variable and the total grain production in North China as the explanatory variable [4,5], and the following regression model of grain sales can be established:

$$\text{Sales}_t = \alpha_1 \cdot \text{Production}_t + \alpha_2 \cdot M_t + \beta_0 + \epsilon_t \tag{3}$$

Where, ϵ_t denotes the error term, which is used to capture fluctuations or other random factors that cannot be explained by explanatory variables.

Regression analysis was performed using MATLAB software, and some of the results are as Table 2 and Fig. 2.

Table 2. Correlation coefficients of the linear regression model for crop yield.

	Numeric value
Intercept	$-1.4808\text{E}-15$
Yield factor	0.92361
R^2	0.853
Adjusted R^2	0.832
Root Mean Square Error	0.41
F statistic	40.6
The intercept of p	1
The yield factor of p	0.000376
The p-value of the F-statistic	0.000376

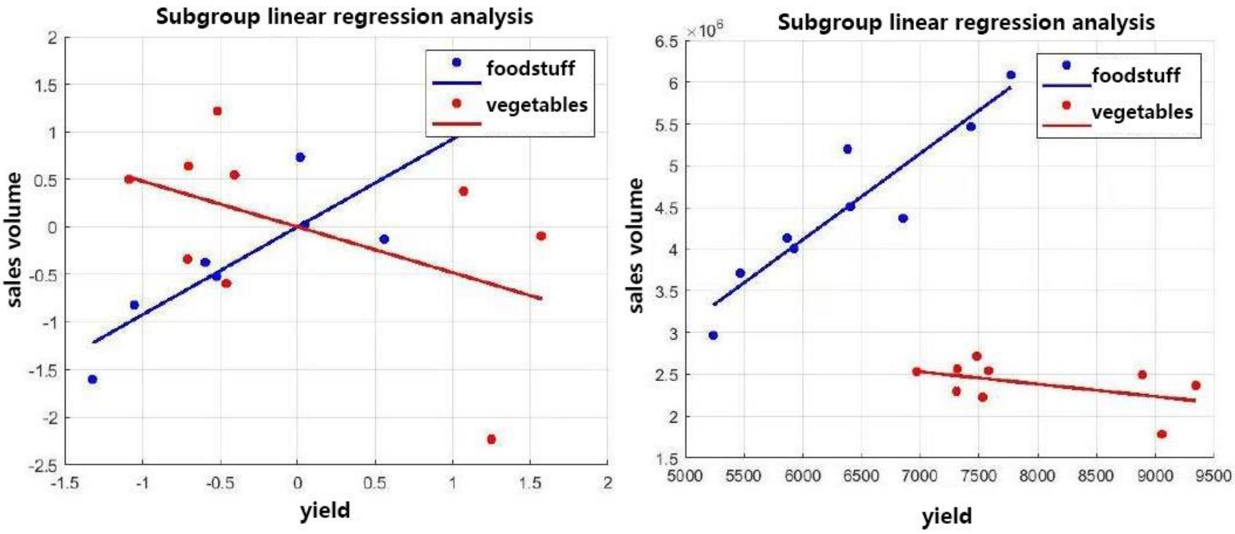

Fig 2. Grouping linear regression results.

Root mean square error is 0.937; R square is 0.231; adjusted R square is 0.121; F-statistic (constant model) is 2.1; p-value =0.19.

When the vegetables were examined, their p-values were 0.19<0.05 and the root mean square error was close to 1, which was not significant, so its impact on crop sales was not considered.

According to the results, the intercept of the regression model is close to 0 and its p-value is 1, indicating that the intercept is not statistically significant and therefore has no substantial impact on the interpretation of the model results. The regression coefficient for yield is 0.92361, which means that for every 1 unit increase in yield, grain sales increase by 0.92361 units on average, all other things being equal. The coefficient has a p-value of 0.000376, indicating that it is statistically highly significant, indicating a very high level of confidence in the impact of production on sales. The coefficient of determination of the model is R^2=0.853 and the adjusted R^2=0.832, indicating that the model can explain 85.3% of the fluctuations in grain sales, with a high degree of fit and strong explanatory power. The F statistic is 40.6, and the corresponding p-value is 0.000376, which verifies the overall significance of the model, indicating that the impact of yield on grain sales is statistically significant and the prediction ability of the model is reliable.

3.2.3. Solving of expected sales of crops

Based on the above regression model, substituting the data on the production of each crop in 2023 can give the expected sales volume for 2023. Since question 1 assumes that the expected sales of crops in 2024-2030 will remain stable in 2023, this set of data can be used in subsequent questions related to expected sales. Part of the predictions obtained using MATLAB are as Table 3.

Table 3. Expected sales of crops.

Crop name	Expected sales volume	Crop name	Expected sales volume
wheat	166599	barley	11439
chinese cabbage	145149	Climb the beans	11323
corn	129217	Elm mushroom	8830
White radish	96766	Lentinula edodes	7167
millet	72553	eggplant	6773
soybean	59253	Beanie	6280
eggplant	37669	Kidney beans	6280
carrot	35452	morel	5086
sweet potato	35452	Oily lettuce	4501
mung bean	34921	Cabbage	3975

4. Optimal Planting Strategy Model

4.1. Regression analysis model

Taking the planting area of crop i on plot k in year j of year t as the decision variable, and the profit of crops planted on all plots as the response variable, the objective function of maximizing the profit obtained from 2024-2030 is taken as follows:

$$Z_1 = \sum_{t=2024}^{2030} \sum_{k=1}^{2} \sum_{i} \left(p_i \cdot \min(y_{i,k,t}, D_i) - d_i \cdot \sum_{j} x_{i,j,k,t} \right) \tag{4}$$

$$Z_2 = \sum_{t=2024}^{2030} \sum_{k=1}^{2} \sum_{i} \left(p_i \cdot \min(y_{i,k,t}, D_i) + 0.5 \cdot p_i \cdot \max(y_{i,k,t} - D_i, 0) - d_i \cdot \sum_{j} x_{i,j,k,t} \right) \tag{5}$$

4.2. Establish constraints

4.2.1. Plot Area Constraints:

Each plot or greenhouse cannot be planted more than its maximum usable area:

$$\sum_{i=1}^{n} x_{i,j,k,t} < S_{j,k}, \forall j, k \tag{6}$$

4.2.2. Total Sales Constraints:

The total sales volume of each crop is the sum of the yield of that crop in all plots and greenhouses:

$$\mathrm{y_{i,t}} = \sum_{k=1}^{m} y_{i,k,t}, \forall i, t \tag{7}$$

m Is the number of plots of land of all certain plot types planted for i crops?

4.2.3. Heavy stubble constraints:

Due to the inability to replant continuously:

$$x_{i,j,k,t} + x_{i,j,k,t-7} \leq D_{j,k} \quad , \forall j, k \tag{8}$$

4.2.4. Legume crop rotation constraints:

Each plot of land must be planted with legume crops at least once in three years (assuming the d-d crop is legumes):

$$\sum_{t=t_o}^{t_o+2} x_{d,j,t} \geq \varepsilon, \forall \mathrm{j}, \quad t_o = 2024{,}2027 \tag{9}$$

4.2.5. Decentralized Management Constraints

In order to facilitate field management, the planting area of each crop per season should not be too spread out and not too small. Set the planting area of each plot to be greater than a lower bound A_{min}, and the total area must not be spread over too much land (set the maximum number of planting plots$N_{\max}$).

4.3. Game Theory Hybrid Particle Model

In this paper, the game theory strategy of multi-agent is introduced, combined with the global search ability of particle swarm optimization, the maximum value of profit is solved under multiple constraints, and the optimal planting strategy is formulated.

Evolutionary game theory combined with particle swarm optimization can simulate the process of population evolution through the strategic adjustment and adaptability of individuals in multiple games, and at the same time, combined with the global search ability of particle swarm optimization. Individuals adjust their strategies according to historical performance and group feedback, and the particle population gradually approaches the global optimal solution in the process of continuous evolution. Finally, the evolutionary stabilization strategy and the global search of particle swarms are combined to achieve the optimal solution of the multi-objective problem. Each particle in the particle swarm corresponds to the individual participating in the evolutionary game, and in order to achieve the goal of maximizing the overall profit in this problem, the overall optimal solution should be adopted. In the evolutionary game, each particle adopts three strategic states to update its own state: relying on its own inertia, relying on its own historical optimal state, and relying on the optimal state obtained by group evolution [6-8].

Set problem parameters such as the number of particles, plots, crops, and seasons, and initialize each particle to a random position and velocity, as well as set inertia weights ω and learning factors $c_1,\ c_2$.

Each particle is updated according to its historical optimal position p_best and global optimal position g_best, and the strategy of each particle is adjusted in combination with the game reward function, and the parameters are controlled ω, c_1, c_2 at the same time.
Nonlinear adaptive tuning is done in the form of the following functions:

$$\begin{gathered}
\varpi(t+1) = (\varpi_{\max} - \varpi_{\min})\exp\left(-\frac{t}{\beta t_{\max}}\right) + \varpi_{\min} \\
c_1(t+1) = (c_{1\,\max} - c_{1\,\min})\exp\left(-\frac{t}{\beta t_{\max}}\right) + c_{1\,\min} \\
c_2(t+1) = (c_{2\max} - c_{2\min})\exp\left(-\frac{t}{\beta t_{\max}}\right) + c_{2\,\min} \\
\beta = \frac{Z_1(t) + Z_2(t)}{Z_3(t) + \Delta}
\end{gathered} \tag{10}$$

Where: $\Delta 1\mathrm{e} - 10$ is to limit the parameter β to be too large, $Z_i(t)(i = 1,2,3 \ldots)$ represents the share of the group adopting different strategies at the tth iteration, which is obtained by the following dynamic replication equation:

$$Z_i(t) = -Z_i(t) \cdot E(t) \cdot K \cdot E^T(t) - E(t) \cdot K \cdot Z_i(t) \tag{11}$$

Where: $E(t)$ is the evolutionary stabilization strategy for this iteration; K is the cost matrix populated by the average return; $f(e_i)$ is the objective value $f(e_i)E(t)$ corresponding to the particle application strategy e_i.

The fitness value (and objective function value) of each particle is calculated, the benefit of the particle in the multi-objective assignment problem is evaluated, and the individual optimal position p_best and global optimal position g_best is updated according to the benefit.

The global optimal solution is updated according to the fitness value of the particles and the game results, and whether the particle population satisfies the termination condition of the multi-objective problem is checked after each iteration.

When a preset termination condition is reached (such as maximum iteration max_inter or return convergence), the final global optimal solution is output, and the particle state and allocation strategy at each time point are saved.

5. Optimal Planting Strategy Model of Monte Carlo Method

5.1. Model Construction

In the improved particle algorithm model based on game theory, only the inertia weight and learning factor change with iteration, so the model lacks consideration of market, climate, and other factors. The Monte Carlo simulation is introduced into the model, which can effectively test the sensitivity of the model to the changes of unknown factors and can be used as a criterion for judging the advantages and disadvantages of the model.

The objective functions and constraints in this section are consistent with the previous sections:

$$Z_1 = \sum_{t=2024}^{2030} \sum_{k=1}^{2} \sum_i \left(p_i \cdot \min(y_{i,k,t}, D_i) - d_i \cdot \sum_j x_{i,j,k,t}\right) \tag{12}$$

For wheat and corn, the annual growth rate of sales is 5% to 10%:

$$\left(S_t^{\text{wheat / corn}} = S_{t-1}^{\text{wheat / corn}} \times \left(1 + g_t^{\text{wheat/corn}}\right)\right. \tag{13}$$

For other plants, the annual sales volume is:

$$S_t^{\text{other crops}} = S_{t-1}^{\text{other crops}} \times 1.05 \tag{14}$$

Vegetable prices are increasing 5% every year:

$$P_t^{\text{vegetables}} = P_{t-1}^{\text{vegetables}} \times 1.05 \tag{15}$$

The price of edible mushrooms is decreasing 1%-5% every year:

$$P_t^{\text{mushrooms}} = P_{t-1}^{\text{mushrooms}} \times \left(1 - r_t^{\text{mushrooms}}\right) \tag{16}$$

There is a limit to the total planting area:

$$\sum_{i=1}^{n} A_t^i \leq A_{\text{total}} \tag{17}$$

Planting risks due to fluctuations in sales prices:

$$\text{Risk} = \sum_{i=1}^{n} \sigma_i \times \left(P_t^i - \mathbb{E}[P_t^i]\right) \tag{18}$$

5.2. Model Solving

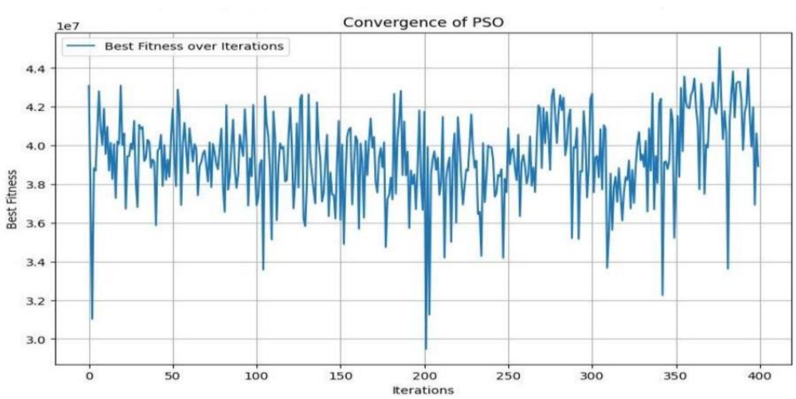

Fig 3. Flowchart of particle swarm optimization using the Monte Carlo method.

As shown in Fig. 3, the test chart obtained by introducing Monte Carlo simulation on the basis of problem 1 is introduced, and it is not difficult to find that the total return corresponding to the optimal solution is always reciprocating with 40 million as the baseline, which is similar to the total return of the optimal solution in problem 1, which can further reflect the effectiveness of the Monte Carlo simulation after the introduction of Monte Carlo simulation.

6. Conclusion:

The optimization model combining game theory and hybrid particle swarm optimization proposed in this paper has been successfully applied to the optimization of farm planting strategies. Accurate linear regression modeling provides reliable data support for the optimization process. Using the global search ability of the hybrid particle swarm optimization (MSF), this paper finds the optimal solution under a variety of realistic constraints, which significantly improves the effect of the planting strategy. Furthermore, the introduction of the Monte Carlo method enables the model to take into account factors such as climate and geographical location, thereby enhancing the accuracy of prediction and the practicability of the model. This study not only verifies the effectiveness of the combination of game theory and hybrid particle swarm optimization in practical applications, but also provides a valuable reference for similar multi-dimensional programming problems. Future work can build on this to explore how to further optimize the model and expand its application to address more complex practical challenges.

References

[1] Liu Jahao, Ju Ronghua. A study on the impact and stability of multi-period price weights on agricultural market supply decisions - based on a second-order price-weighted spiderweb model [J/OL]. Price theory and practice. Practice: 1-6[2024-09-08]. https://doi.org/10.19851/j.cnki.CN11-1010/F.2024.08.196.

[2] Sun Chuanheng, YU Hua Jing, XU Daming, et al. Research progress and prospect of blockchain traceability technology in agricultural supply chain [J]. Journal of Agricultural Machinery, 2021, 52(1): 1-13.

[3] Liu Hebing, **Jingjing, MA Xinming, et al. Research on price prediction of agricultural products based on EMD-ELM model [J]. Journal of Agricultural Big Data, 2020, 2(3): 68-74.

[4] Zhao Rongyang, Deng Yun, Ou Gaofei. Design of big data platform for agricultural products price prediction based on exponential smoothing [J]. Internet of Things Technology, 2024, 14(08): 113116.DOI: 10.16667/j.issn.2095-1302.2024.08.029.

[5] Ximan Huang, Tongxin Deng, Mengyao Cha, et al. A study on chicken price prediction in Jiangsu Province based on PSO-RBF neural network [J]. Modern Business, 2024(13): 3-6.DOI: 10. 14097/ j. cnki. 5392/ 2024.13.025.

[6] Rongjie Wang, Liang Zhang. Multi-UAV task allocation based on hybrid particle swarm with game theory [J/OL]. Computer Science: 110[20240908]. Http: //kns.cnki.net/kcms/detail/50.1075.tp. 20240824. 1304.013. Html.

[7] Wang Xu, JI Weidong, Zhou Guohui. Optimisation of fault indicator configuration based on cooperative game particle swarm algorithm [J]. Journal of System Simulation, 2023, 35(6): 1278.

[8] Yao Tuozhong. Game analysis of power supply chain based on particle swarm optimisation and improved ant colony algorithm [J]. Zhejiang Electric Power, 2022, 41(9).