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Optimizing Enterprise Marketing Project Portfolios Using Fuzzy Ant Colony Optimization

Jian Mao

Jian Mao*
State Grid Hunan Electric Power CO.LTD
Changsha 410000, China
*Corresponding author: maojian20230408@163.com
andonie@cwu.edu

Abstract

Enterprise marketing project portfolio optimization is important for business competitiveness, but involves multiple uncertain factors. An integrated model using fuzzy rules was proposed in this paper to enhance ant colony optimization. The fuzzy ant colony algorithm effectively handled ambiguity in project costs, returns, and risks when selecting an optimal portfolio of marketing initiatives. Experiments demonstrated the algorithm efficiency in converging towards high-quality solutions. Case studies indicated the model helped boost customer loyalty and profits through tailored marketing strategies, outperforming conventional approaches. The fuzzy optimization provides an effective decision-making framework for enterprises to maximize marketing effectiveness.

Keywords: Enterprise; Marketing projects; Combination optimization; Ant colony fuzzy rules.

1 Introduction

With the increasingly fierce competition among enterprises, effective optimization of marketing project portfolio has become an important strategy for enterprises to improve competitiveness and gain market share. In the past few decades, machine learning played an important role in providing enterprises with many optimization solutions [1, 2]. In machine learning, the optimization model of enterprise marketing project portfolio based on metaheuristic algorithms has become an important method. The optimization model of enterprise marketing project portfolio refers to maximizing the marketing revenue of the enterprise by selecting the most effective marketing activity portfolio under limited resource constraints. In traditional enterprise marketing project portfolio optimization, a single-optimization model is often applied. However, the market constantly changes with customer preferences, competitor strategies, and external economic conditions in practical applications. A single-optimization model cannot meet complex decision-making needs. Accurate marketing project portfolio decision-making can help companies quickly deal with market changes, accurately position consumer needs, and increase market share and corporate profits. Therefore, uncertainty and fuzziness need to be taken into account to provide more robust optimization results [3, 4, 5]. Ant Colony Optimization (ACO) is a heuristic algorithm based on simulating ant behavior and information exchange.

It is based on the distributed computing of ant colonies and the tracking and updating mechanism of pheromones, which simulates the intelligent behavior of ants in solving the optimal solution [6, 7]. When optimizing enterprise marketing project portfolio, ACO can flexibly adapt to different situations and decision objectives, which has good robustness and global optimization ability. In view of this, first, the study designed an enterprise marketing project portfolio optimization model based on product marketing decisions. Then the pheromone update method of ACO algorithm was optimized through fuzzy rules, and a Fuzzy Ant Colony Optimization (FACO) algorithm was designed. Finally, this algorithm was applied to the designed model, providing effective marketing strategy guidance for enterprises and improving their competitiveness. This algorithm can handle the optimization problem of enterprise marketing project portfolio more flexibly. Meanwhile, it can effectively deal with the uncertainty and fuzziness of the market, providing enterprises with stable and efficient marketing strategies. The innovation of the research lies in the introduction of fuzzy rules to dynamically adjust the updating strategy of pheromones based on the traditional algorithm, thereby improving the algorithm's adaptability and global search ability in changing market environments. The contribution of the research lies in providing enterprises with an effective marketing project portfolio optimization strategy to cope with market changes. Meanwhile, it contributes to expanding the application of machine learning algorithms in enterprise marketing and providing new ideas for subsequent related research. This article mainly consists of five parts. The first part is the background of optimizing enterprise marketing project portfolio. The second part is a review of the current research status of enterprise marketing project optimization. The third part is research methodology, which first constructs an enterprise marketing project portfolio optimization model, and then designs a combination optimization model solution method based on the FACO algorithm. The fourth part is results and discussion, including the performance analysis of the FACO algorithm and the analysis of the model application effect. The fifth part summarizes the entire study and the shortcomings of the research.

2 Related works

In modern business environments, the combination optimization of enterprise marketing projects is important. Enterprises make the best combination of various marketing factors based on their development situations, which promotes effective coordination among them and maximizing the profits of companies. However, the market is becoming more competitive. Various complex and uncertain factors in the market environment may affect the implementation of marketing strategies. Therefore, it has become a challenge to dynamically adjust the marketing program portfolio based on the corporate resources and market demand to achieve maximum marketing effects. In recent years, many scholars and business professionals have conducted numerous studies on optimizing the combination of enterprise marketing projects. Mavrotas G and other researchers designed a novel method to simulate the uncertainty in R&D project portfolio selection. The method combined multi-criteria analysis, mathematical programming, and Monte Carlo construction of decision wheels within the iterative three-way framework. The results showed that this method provided a certainty for selecting and rejecting projects [8]. Kock A et al. designed a project portfolio management system to improve the performance of enterprise project portfolios, which increased the success of project portfolios by improving the management quality of the project portfolio. The results showed that the system had lower task complexity [9]. Rasoulzadeh M and other scholars designed a project portfolio optimization method based on fuzzy data envelopment analysis model to quantify and measure enterprise marketing project management. The method used linear methods and introduced fuzzy set theory to select the optimal investment portfolio. The results showed that the method achieved good performance ranking and evaluation capabilities [10]. Bai L and other researchers designed a dynamic evaluation model based on system dynamics to analyze and optimize the returns of enterprise marketing projects. The model took into account the implicit benefits generated by the synergistic effects between different project components. The results showed that the model effectively strengthened the management of project portfolio returns [11]. Baqeri K et al. designed a multi-objective model for selecting project portfolios to determine the most objective alignment with objectives in enterprise marketing projects. This model minimized risks in project execution by reflecting the stance, goals, and priorities of the organization. The results showed that this method effectively improved the efficiency and quality [12]. Afshar M R and other scholars designed a project portfolio planning method using a mixed-integer linear programming model to solve the problem of selecting and assigning the optimal subcontractor in multiple construction projects. The method minimized project costs in different situations and applied an algebraic modeling system for it. The results showed that the model was reliable [13].

Rasoulzadeh M and other scholars designed a multi-objective method based on the Markowitz mean-variance model and cross-data envelopment analysis to solve the uncertainty in enterprise marketing projects. The method combined Markowitz with the data envelopment model, and intuitive fuzzy numbers were used to calculate the optimal combination. The results showed that this method had high computational efficiency [14]. Burney SMA and other scholars designed a particle swarm optimization algorithm based on fuzzy granularity clustering to effectively optimize the marketing mix of enterprises. The algorithm formed clusters through fuzzy particle swarm optimization and granularity calculation, and the benchmark index value of the algorithm was better than other methods [15]. Shi W et al. designed a co-evolutionary distribution estimation algorithm using divide and conquer strategy to achieve the optimal allocation of marketing mix for enterprise projects. The algorithm decomposed the group combination problem into individual problems to reduce the dimensions of the optimization problem. The results showed that this method effectively solved combination optimization problems [16]. Nieto A and other researchers designed a genetic simulation heuristic algorithm to solve the optimization problem of marketing mix in enterprises with debt. It integrated Monte Carlo simulation at different stages of the genetic algorithm to maximize the expectation under uncertainty. The results showed that this algorithm had high computational efficiency [17]. Deliktaş D designed a fuzzy multi-objective genetic algorithm based on cardinality constraints for decision-making in portfolio optimization under fuzzy parameters. The algorithm optimized portfolios through fuzzy multi-objective methods and mean variance sorting cardinality constraints. The results showed that the algorithm had high computational accuracy [18]. Chou Y H et al. designed a weighted optimization model based on trend ratio and sentiment index to optimize investment portfolios for stable returns and reduce overall risk. The model took into account the volatility of the portfolio comprehensively and automatically constructs them through quantum non-gates. The results showed that the algorithm had high accuracy and efficiency [19].

In summary, a number of combinatorial optimization methods have been proposed by many scholars in the enterprise marketing project portfolio optimization to improve resource allocation and enhance marketing performance. However, these methods still suffer from high computational complexity. Therefore, this study introduces fuzzy rules on the basis of traditional ACO algorithms and designs a FACO algorithm for solving the combination optimization model of enterprise marketing models to improve the optimization effect and efficiency.

3 Research methodology

This chapter mainly elaborates on the construction of an enterprise marketing project optimization model based on the FACO algorithm. The combination optimization model was designed in the first section, and the second section is the improvement and function design of the ACO algorithm.

3.1 Design of optimization model for enterprise marketing project portfolio

In complex market environments, enterprises not only need to consider the effective allocation of internal resources, but also need to monitor market dynamics and behavioral changes. Therefore, it is important for consumers to develop the optimal marketing strategy combination. The ability of enterprises to meet their set marketing goals can be maximized by implementing precise strategic planning to improve the effectiveness of marketing activities and achieve the strategic goals of the enterprise, thereby standing out in a fiercely competitive market environment [20, 21]. Meanwhile, multiple factors such as product, price, sales channels, and promotion need to be considered in the combination optimization of enterprise marketing. The marketing mix of an enterprise requires comprehensive consideration of different factors and optimization based on market demand and competition. Its specific composition is shown in Figure 1.

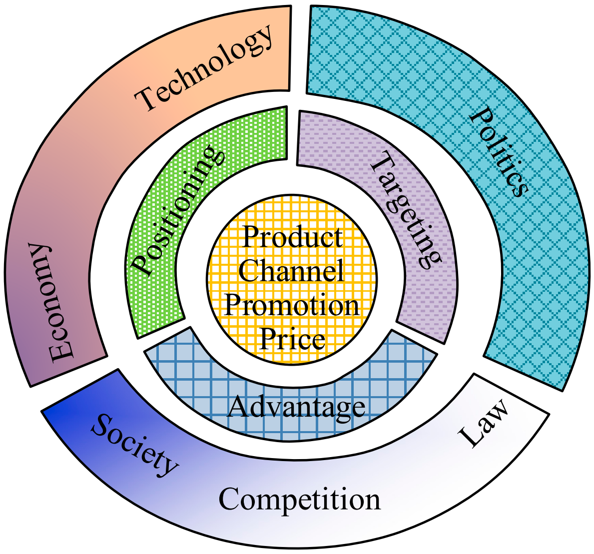

Figure 1: Enterprise marketing mix model

In Figure 1, the marketing mix is an organic whole. Enterprises need to comprehensively consider different factors and optimize them based on market demand and competitive conditions. Therefore, the study first establishes an objective function for product portfolio decision-making in the marketing process based on these factors. Meanwhile, different product marketing decisions can be divided into long-term and short-term decisions. The model expression for long-term decisions is shown in equation (1).

$$Z_L = \sum_i (p_i - b_i)X_i - \sum_{i,j} \phi q_{ij} \lambda \tag{1}$$

In equation (1), Z represents the objective function of long-term decision-making, p_i represents the market sales price of marketing products i, b_i represents the additional cost required for each marketing product, X_i represents the quantity of marketing products, ϕ represents the resources or budget allocated for enterprise marketing projects, q_{ij} represents the demand for different projects in the marketing project portfolio, j represents the j-th marketing project, λ represents a constant, and its value range is within [0,1]. The method for short-term decision-making is shown in equation (2).

$$Z_s = \sum_i (p_i - b_i)X_i - \sum_i \phi Q \tag{2}$$

In equation (2), Z_s represents the objective function of short-term decision-making and Q represents the sales volume of the enterprise. However, it is not enough to only use long-term and short-term decision models if marketing mix decisions are made solely based on time. Because the length of time periods is a relatively fuzzy concept that is difficult to accurately measure. Meanwhile, both long-term and short-term decision models do not consider the time variable. Therefore, the study combines the two models into a mixed decision model, whose expression is shown in equation (3).

$$Y = \sum_{j=1}^{N} (p_i - Q_0)X_i - \sum_{j=1}^{J}\sum_{k=1}^{K} \phi Q \tag{3}$$

In equation (3), Y represents the objective function of the mixed decision model, Q_0 represents the expected sales volume of the enterprise, J represents the total marketing projects, and k represents the market demand for marketing products, $k \in K$. The enterprise marketing mix decision model is shown in Figure 2.

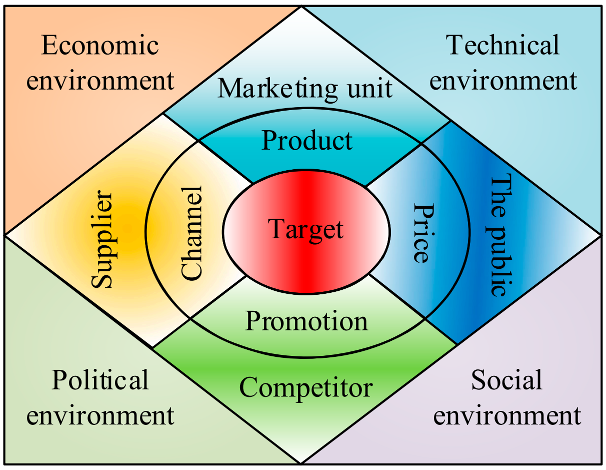

Figure 2: Enterprise marketing mix model

Enterprise marketing decision-making is not just a simple strategy formulation, but a complex dynamic process. It mainly utilizes internal controllable factors such as marketing strategies, product pricing, promotional activities, etc. to adapt to the constantly changing external environment. Faced with external uncontrollable factors such as market trends, competitors, consumer demands, etc., enterprises need to demonstrate active and flexible response capabilities to achieve transactions and achieve personal and corporate goals. However, it is necessary to eliminate the differences between the models to mix them. To address this issue, parameters in the model are defined to clarify the funding investment for each project in marketing, as expressed in equation (4).

$$\begin{cases} Q = R_{ij} + W_{ij} \\ \sum_{j=1}^{J} X_i q_{ij} = R_u + W_u \\ 0 \leq R_u \leq R_{ij} \\ 0 \leq W_u \leq W_{ij} \\ X_i \geq 0 \end{cases} \tag{4}$$

In equation (4), R_{ij} represents the funds available for marketing projects in Q, W_{ij} represents the project funds that cannot be freely allocated in Q, R_u represents the actual investment of funds in enterprise marketing, and W_u represents the budget of funds in enterprise marketing. Different enterprises can adjust parameters based on their financial situation. The next step is to calculate the actual range of capital investment, expressed in equation (5).

$$R_u = \begin{cases} 0, \sum_{i=1}^{X_i} X_{ij} q_{ij} \leq W_{ij} \\ \sum_{i=1}^{X_i} X_{ij} q_{ij} - W_{ij}, \sum_{i=1}^{X_i} X_{ij} q_{ij} > W_{ij} \end{cases} \tag{5}$$

The study aims to avoid formulating overly idealized marketing plans by determining the actual scope of investment. Therefore, the allocation of marketing funds can be better controlled and optimized, the efficiency of marketing activities can be improved, and the strategic goals of the enterprise can be achieved. The next step is to define the constraint conditions for the optimization model of enterprise marketing mix, and its expression is shown in equation (6).

$$\begin{cases} J = Max \sum_{i,j} \eta_{ij} \xi_{ij} \\ \eta_{ij} = T_i - \tau \psi_{ij} \end{cases} \tag{6}$$

In equation (6), η_{ij} represents the profit coefficient in the marketing project, ξ_{ij} represents the penalty coefficient, and its value is 0 or 1. T_i represents the target profit of a marketing project, $\tau\psi_{ij}$ represents the correlation and impact between different marketing projects, and τ represents the correlation factor. Finally, the penalty coefficient is constrained, and its constraint conditions are shown in equation (7).

$$\sum_{i\in S}\sum_{j\in S}\xi_{ij} \leq |S|-1, 2 \leq |S| \leq X_i - 1 \tag{7}$$

In equation (7), S represents the total number of marketing project combinations. Under constraints, enterprises can flexibly allocate marketing budgets, respond to market changes, and adjust their internal marketing strategies. At this point, the construction of the enterprise marketing project portfolio optimization model is completed, and its framework is shown in Figure 3.

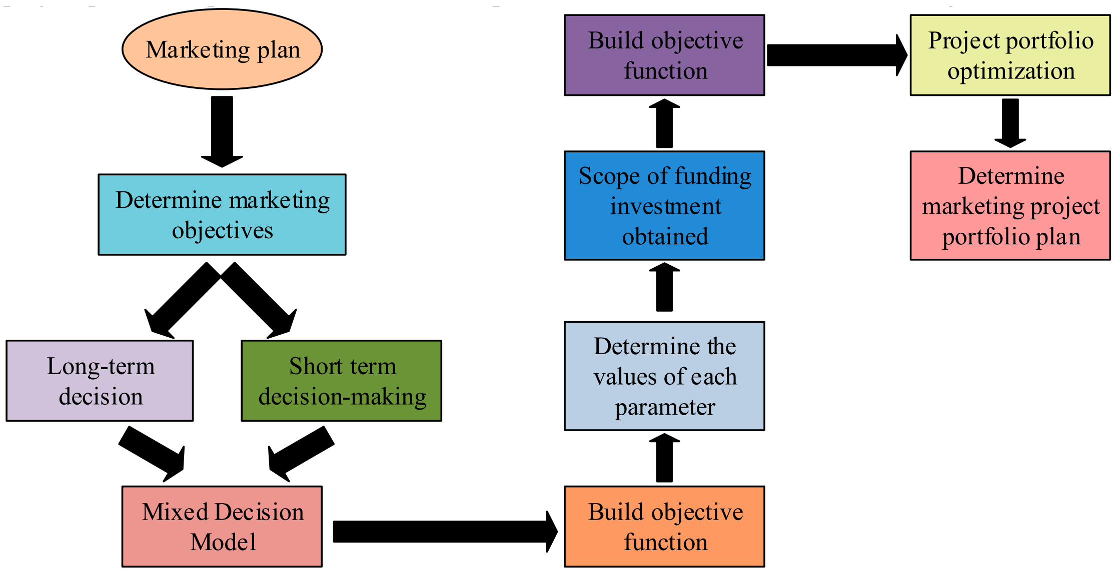

Figure 3: The framework of optimization model for enterprise marketing project portfolio

3.2 Solution algorithm for improved ACO combination optimization model based on fuzzy rules

Due to the uncertainty and fuzziness of factors in the combination of enterprise marketing strategies, it is difficult to describe them accurately using mathematical models. Therefore, the flexible optimization algorithms are used to find the optimal marketing project portfolio in complex and uncertain environments to solve such problems. Common optimization methods include greedy algorithms, dynamic programming, genetic algorithms, simulated annealing algorithms, ACO algorithms, etc. [22, 23, 24]. The ACO algorithm is adopted in this study to optimize the enterprise marketing project portfolio. However, traditional algorithms have the problems of easily falling into local optima and time-consuming search process. Therefore, the study improves the search strategy of traditional algorithms and introduces fuzzy rules to optimize its information updating method to design the FACO algorithm. The fuzzy logic effectively avoids algorithms falling into local optima early and enhances their search ability. Compared with traditional algorithms, FACO can better understand the uncertainty and fuzziness of space, and the search efficiency is improved. The process of traditional ACO is shown in Figure 4.

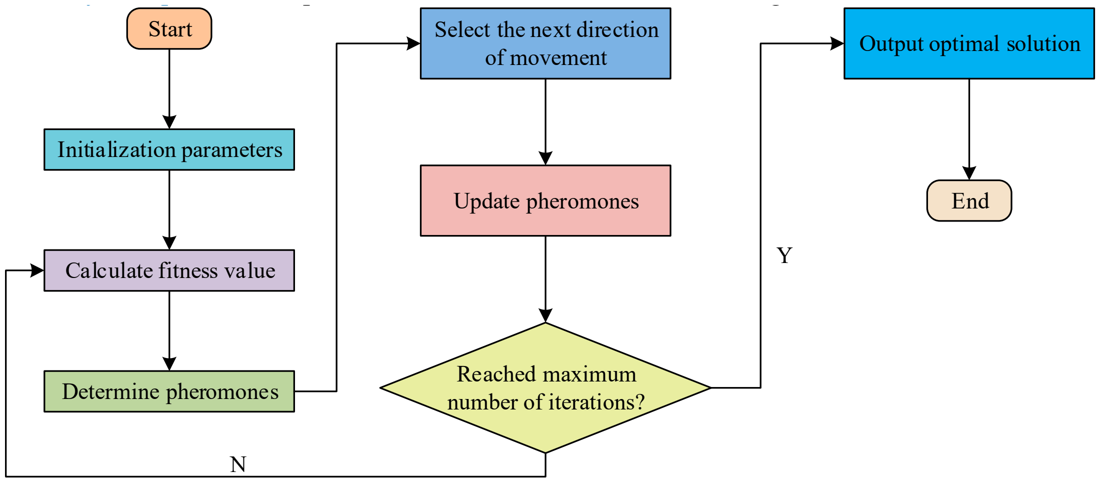

Figure 4: The process of traditional ant colony algorithm

In Figure 4, each parameter is first initialized, and then the movement path of the ant colony is constructed. At the initial moment $t_0 = 0$, when the number of pheromones on each path is the same, the state transition probability of ants from one node to another is shown in equation (8).

$$P_{i,j}^{k}(t) = \begin{cases} \frac{[\gamma_{ij}(t)]^{\alpha}[\varepsilon_{ij}(t)]^{\beta}}{\sum_{s \in J_k(i)} [\gamma_{is}(t)]^{\alpha}[\varepsilon_{is}]^{\beta}}, j \in J_k(i) \\ 0, j \notin J_k(i) \end{cases} \tag{8}$$

In equation (8), $P_{i,j}^{k}$ represents the probability of ant k moving from node i to node j, t represents the time, γ_{ij} represents pheromone concentration, ε_{ij} represents the heuristic function, α represents an information heuristic factor, β represents the expected heuristic factor, and J_k represents the set of nodes that ants can choose in the next step. α reflects the relative importance of pheromones. β reflects the relative importance of visibility, which is the distance between nodes. The larger α and β, the greater the probability of ants selecting the closest node to themselves. During the movement of ants, to prevent leaving too many pheromones on the path and masking the heuristic information, each ant needs to update and process the remaining information after completing its traversal to improve search efficiency. The iterative formula for updating pheromones is shown in equation (9).

$$\begin{cases} \gamma_{ij}(t+n) = (1-\rho)\gamma_{ij}(t) + \Delta\gamma_{ij} \\ \Delta\gamma_{ij} = \sum_{k=1}^{m} \Delta\gamma_{ij}^{k} \end{cases} \tag{9}$$

In equation (9), ρ represents the pheromone volatilization factor, $\Delta\gamma_{ij}$ represents the increase in pheromones along the path (i, j) after a search is completed, and m represents the total number of ants. The calculation method for the increase in information is shown in equation (10).

$$\Delta\gamma_{ij} \begin{cases} \frac{Q}{L_k} \\ 0 \end{cases} \tag{10}$$

In equation (10), Q represents the total pheromones released by an ant cycle, and L_k represents the total length of the path passed by the k-th ant. When ants pass through a path (i, j), $\Delta\gamma_{ij} = \frac{Q}{L_k}$. When ants do not pass through a path (i, j), $\Delta\gamma_{ij} = 0$. Then, the search strategy of the ACO algorithm is improved. During the search, the ants traverse all nodes to directly generate feasible solutions. The improved state transition probability formula is shown in equation (11).

$$P_i = \begin{cases} \frac{x_i \cdot \gamma_i(t)}{\sum_{k \in C} x_k \cdot \gamma_i(t)}, i \in C \\ 0, i \notin C \end{cases} \tag{11}$$

In equation (11), P_i represents the probability of ant state transition from one node to another after optimization, and C represents the set of available paths for ant movement. However, the ACO algorithm is prone to stagnation. All individuals find identical solutions and cannot further find the solution space after search, which is not conducive to discovering better solutions. Therefore, the study introduces fuzzy rules to fuzzify input values to optimize the pheromone update method. The fuzzy control framework is shown in Figure 5.

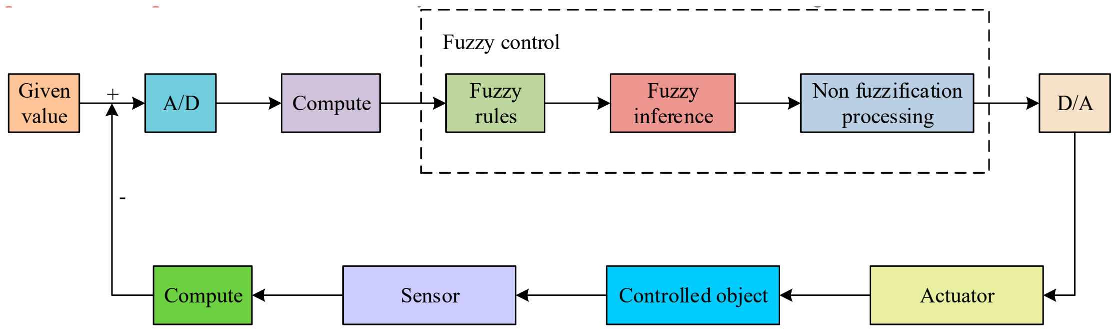

Figure 5: Fuzzy control framework diagram

Fuzzy logic is a mathematical method used to deal with fuzzy or uncertain problems, which uses fuzzy sets to study fuzzy thinking, language forms, and their laws [25, 26]. In fuzzy logic, the first step is to determine rules, which are usually represented by symbols, as shown in equation (12).

$$IF\ x\ isA_i\ AND\ y\ is\ B_i\ THEN\ z\ is\ C_i \tag{12}$$

In equation (12), x, y, and z represent variables. A_i, B_i, and C_i represent fuzzy sets of each variable. Then, the quality and iteration of the ant colony algorithm solution are used as input variables and mapped to the corresponding fuzzy set. Then, a fuzzy subset of fuzzy variables is formed through membership functions, and the selection of triangle functions as membership functions is studied. Its expression is shown in equation (13).

$$y_A(x,a,b,c) = \begin{cases} 0, x < a \\ \dfrac{x-a}{b-a}, a \le x \le b \\ \dfrac{c-x}{c-a}, b \le x \le c \\ 0, x > c \end{cases} \tag{13}$$

In equation (13), y_A represents the value of the triangle function. a, b, and c represent three vertices of the triangle. The next step is to customize control rules based on the needs and characteristics of enterprise marketing projects, and fuzzify them through mean fuzzy processing. The calculation is shown in equation (14).

$$\frac{y}{x - \frac{(a+b)}{2}} = \frac{2n}{b-a} \tag{14}$$

In equation (14), the range of x is controlled within the interval $[a, b]$, and the range of y after fuzzification is $[-n, n]$. Finally, the number of solutions involved in pheromone updating is used as the output of the fuzzy controller. The optimized pheromone updating strategy calculation method is shown in equation (15).

$$\gamma_i(t+1) = (1-\rho)\gamma_i(t) + \sum_{\theta=1}^{L} \Delta\gamma_i^{\theta}(t) \tag{15}$$

In equation (15), L represents the number of solutions updated with pheromones, and θ represents the number of optimal ants. The process of FACO algorithm is shown in Figure 6.

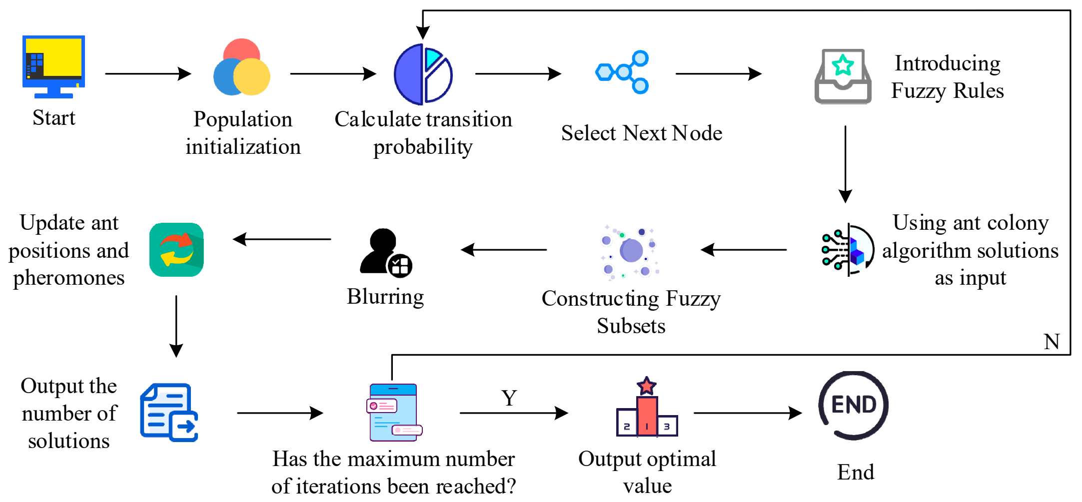

Figure 6: FACO algorithm flowchart

In Figure 6, the population is first initialized, the state transition probability of the ants is calculated, and the next node is selected based on the transition probability. Then, the solution of the ACO algorithm is used as input to the fuzzy logic system, and the ant position and pheromones are updated based on the established fuzzy rules. Finally, the solution is output to determine whether it meets the termination condition. If it does, the optimal solution is output. If it does not, the iteration continues.

4 Results and discussion

This chapter mainly introduces the experimental results analysis of an enterprise marketing project optimization model based on the FACO algorithm. The first section is the performance analysis of the algorithm, and the second section is the application effect analysis of the optimization model.

4.1 Performance analysis of FACO algorithm

The study first used grid search to calculate the optimal and average solutions under different information heuristic factors and expected heuristic factors in the Eil51 dataset to determine the parameter values. The performance of the designed enterprise marketing project portfolio optimization model was verified. The grid search method searched for all possible parameter combinations by specifying a candidate value list of hyperparameters. Each set of parameters was trained and evaluated. Finally, the parameter combination with the best performance was selected as the final hyperparameter of the model. The results are shown in Figure 7.

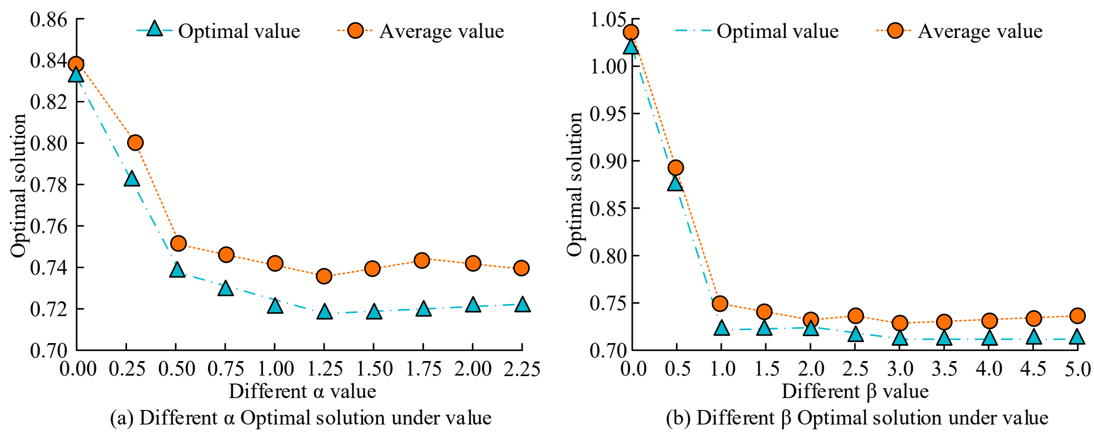

Figure 7: Optimization curve of improved GOA algorithm in four test functions

From Figure 7 (a), when the information heuristic factor $\alpha = 1.25$, the minimum value of the optimal solution was 0.72 and the average solution was 0.74. In Figure 7 (b), when the expected heuristic factor $\beta = 3.0$, the minimum value of the optimal solution was 0.71, and the average solution was 0.74. The above results indicated that the solution performance of the design algorithm was good. The optimal parameter values were determined, $\alpha = 1.25$, and $\beta = 3.0$. The next step was to select a set of data in the Eil51 dataset as the test set. It was divided into 6 categories. The loss curve of the FACO algorithm was calculated. This algorithm was compared with the traditional algorithm. The convergence curves of the two algorithms are shown in Figure 8.

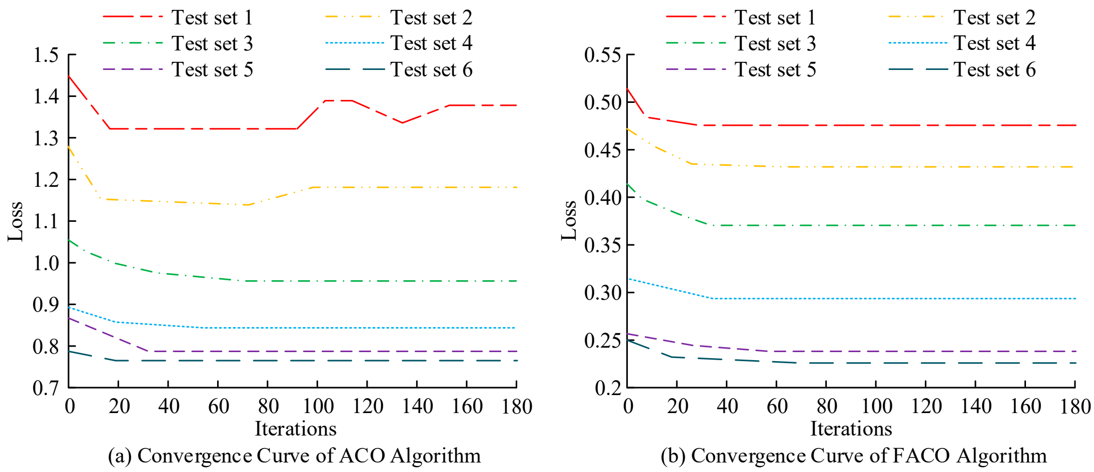

Figure 8: Optimization curve of improved AOC algorithm in four test functions

From Figure 8, in test set 1, the minimum loss value of the traditional algorithm was 1.32, and the minimum loss value of the improved algorithm was 0.47. In test set 2, the minimum loss values for the traditional algorithm were 1.15 and the minimum loss values for the improved algorithm were 0.43, respectively. In test set 3, the loss value of the traditional algorithm when the loss curve reached stability was 0.97, and the loss value of the improved algorithm when the loss curve tended to flatten was 0.37. In test set 4, the loss value of the traditional algorithm when the loss curve tended to stabilize was 0.80, and the loss value of the improved algorithm when the loss curve reached stability was 0.29. In test set 5, the loss value of the traditional algorithm when the loss curve tended to flatten was 0.77, and the loss value of the improved algorithm when the loss curve tended to flatten was 0.24. In test set 6, the minimum loss value of the traditional algorithm was 0.76, and the minimum loss value of the improved algorithm was 0.23. The above results indicate that the improved algorithm FACO performed well on different test sets, and its loss curve did not show significant fluctuations, proving its good stability. The Kaggle dataset is an open-source dataset that contains many real-world data related to marketing. Therefore, the study selected marketing data from 6 e-commerce platforms in a certain month in the Kaggle dataset, trained the FACO algorithm, and conducted error analysis. The results are shown in Table 1.

Table 1: Error analysis of two algorithms

Test set	Actual value	Analog value	Error (%)
Platform 1	0.31	0.3923	0.265
Platform 2	0.22	0.2376	0.080
Platform 3	0.10	0.1023	0.002
Platform 4	0.07	0.0796	0.137
Platform 5	0.13	0.1459	0.122
Platform 6	0.08	0.0943	0.179

From Table 1, in the six test sets, the error range of the test set was 0.002%-0.265%. Platform 1 had the highest error value, with an error of 0.265%, and platform 3 had the lowest error value, with an error of 0.002%. The above results indicated that the FACO algorithm had a small error in predicting enterprise marketing project portfolios and provided more accurate results.

5 Analysis of the practical application effect of marketing project portfolio optimization model

The study first calculated the risk results of the model under different profit preferences to verify the effectiveness of designing an enterprise marketing project portfolio model in practical applications. Meanwhile, the risk level of marketing projects was calculated from three aspects: product, channel, and promotion. The results are shown in Figure 9.

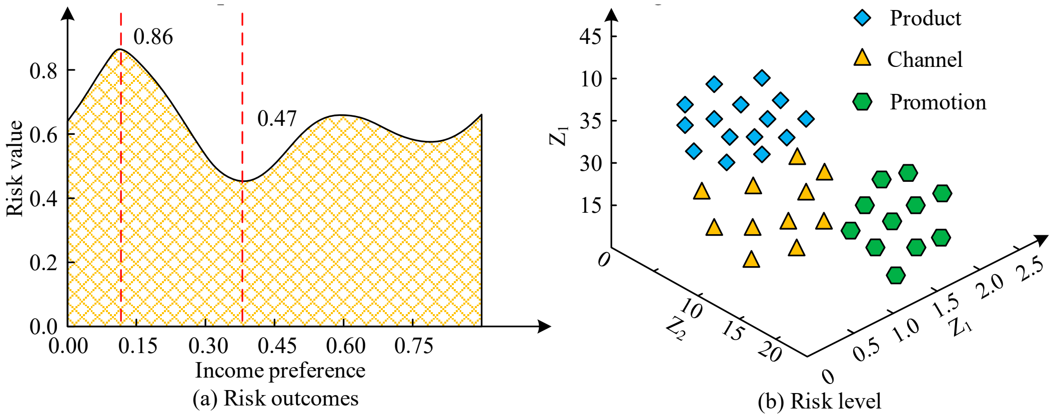

Figure 9: Risk outcomes and risk levels

From Figure 9 (a), as the preference for returns increased, the risk value showed a fluctuating trend. When the return preference was 0.15, the maximum risk value was 0.86. When the return preference was 0.375, the minimum risk value was 0.47. The designed enterprise marketing project portfolio model effectively evaluated the level of risk under different profit preferences. In Figure 9 (b), the risk levels of products, channels, and promotions were evenly distributed and no clustering occurs. When formulating a marketing project portfolio, it was necessary to fully consider the risks in different aspects and reduce the overall risk by allocating resources reasonably. The above results indicated that when formulating marketing strategies, enterprises needed to balance the relationship between returns and risks and find a balance point to maximize returns and control risks. Enterprises often attract customers through a series of marketing project strategies. The study adopted three strategies: promotion, improving quality, and expanding sales channels. These three strategies were combined in pairs to generate six marketing mix strategies. Then, customer loyalty was verified from three aspects: service, channel, and quality, which was compared with the original strategy. Meanwhile, the P-values of different strategies compared with the original strategy were calculated through t-test to verify the difference between these two strategies. The significance test standard was set to 0.05. If $P<0.05$, it indicates that the difference is statistically significant. If $P>0.05$, it indicates that the difference is not statistically significant and is comparable. The results are shown in Table 2.

Table 2: Customer loyalty based on different marketing mix strategies

Marketing mix	Give service to	Channel	Quality	P value	Loyalty
Promotion	96	86	86	<0.05	86
Expand channels	91	85	89	<0.05	86
Improving quality	91	89	86	<0.05	91
Promotion and quality improvement	96	89	84	<0.05	136
Improving quality and expanding channels	86	91	91	<0.05	220
Promotion and channel expansion	96	86	91	<0.05	151
Original strategy	90	85	85	/	80

From Table 2, the P-values between different strategies and the original strategy after t-test were all less than 0.05, indicating that the difference between the two groups was statistically significant. The customer loyalty levels when using 7 marketing mix strategies were 86, 86, 91, 136, 220, 151, and 80, respectively. The customer loyalty of the three strategies of promotion, improving quality, and expanding channels, as well as their combination strategies, was higher than the original strategy. Meanwhile, when there was quality improvement in marketing strategies, customer loyalty was significantly higher than marketing strategies that did not improve quality. The above results indicated that customers paid more attention to improving product quality, indicating that enterprises should focus on product quality when formulating marketing strategies, and a combination of multiple strategies could be used to attract and retain customers. Finally, the designed model was evaluated based on the relationship between net profit and cumulative funds in the enterprise project marketing portfolio. The results of the traditional ACO algorithm-based enterprise marketing project portfolio optimization model were compared to the designed model. The results are shown in Figure 10.

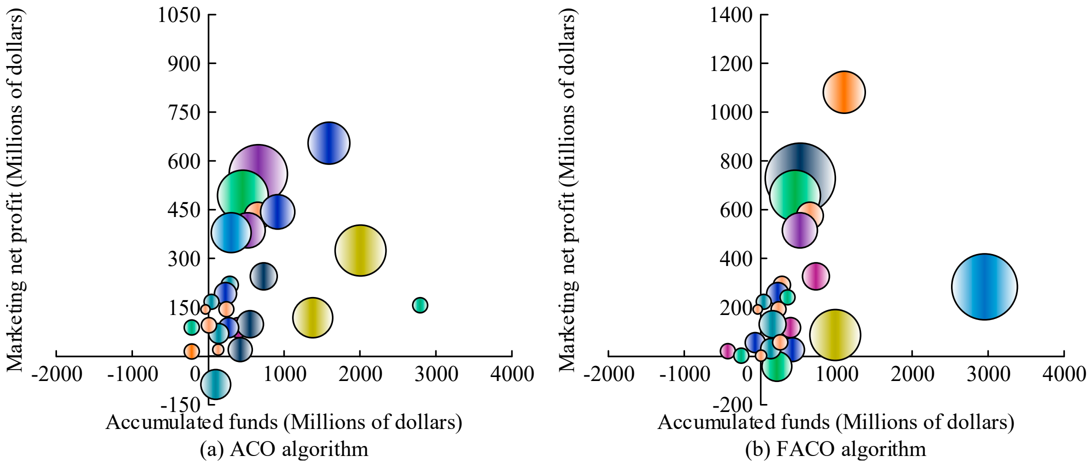

Figure 10: The relationship between net profit and accumulated funds

From Figure 10 (a), the net profit obtained from marketing ranged from -150 million to 750 million US dollars in the enterprise marketing project portfolio optimization model based on the traditional ACO algorithm. In Figure 10 (b), the net profit obtained from marketing ranged from -100 million to 120 million US dollars in the enterprise marketing project portfolio optimization model based on the FACO algorithm. Under the same investment conditions, the net profit of the enterprise marketing project portfolio optimization model based on the FACO algorithm was significantly higher than that of the enterprise marketing project portfolio optimization model based on the traditional algorithm. The above results indicate that the improved algorithm was more precise and effective in project selection and resource allocation, which helped enterprises make wiser decisions and improve their profitability.

5.1 Conclusion

In conclusion, the FACO model constructed in this paper provided an efficient and practical method for enterprises to optimize marketing project portfolios under uncertainty. The integration of fuzzy rules to guide the algorithm optimization proves highly effective. This approach can help managers select the ideal combinations of marketing initiatives that maximize expected returns given acceptable levels of risk and budget constraints. The fuzzy optimization technique can enhance the competitiveness and profitability of enterprises across industries. Adaptive parameter tuning and ensemble techniques can be explored to further improve model robustness.

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