The Application of Cognitive Decision-Making Algorithm in Cross-Border e-Commerce Digital Marketing

Xuehui Wang
International School, Zibo Vocational Institute, Zibo, 255000, China

***Abstract*—Extensive global research aims to improve digital marketing profits through pricing decision-making and optimization. A dual word-of-mouth diffusion pricing model is developed for cross-border e-commerce, addressing word-of-mouth accumulation and information diffusion effects. The traditional artificial bee colony algorithm is optimized with security domain search and information diffusion profiles, enhancing global search capabilities. Performance tests reveal that word-of-mouth scale significantly influences cross-border e-commerce profits, increasing with scale coefficient, consumer conversions, and optimal profits. The proposed algorithms demonstrate high efficiency and convergence rates, surpassing common iterations and benefits in the clothing pricing problem. The comprehensive imitation effect is -0.14, and the word-of-mouth scale effect is 1.34. Pre-sale and sales prices for clothing are set at 347.49 and 641.393, respectively. Similarly, in pricing cross-border e-commerce electronic products, the algorithm achieves optimal profits after 230 iterations, surpassing other algorithms. Overall, the proposed model exhibits superior computational performance in cross-border e-commerce pricing decision-making compared to conventional approaches.**

***Keywords*—Cross-border e-commerce; decision-making; pricing issues; optimization algorithms; ABO**

I. Introduction

With the year-on-year increase in Internet users, e-commerce, especially cross-border e-commerce (CBEC), has developed rapidly in the context of the normalisation of the new crown epidemic. The spread of the epidemic and the preventive and control measures of various countries have had a serious impact on international trade activities. The existing supply chain and industrial chain have been obstructed. The game between China and the United States and the changes in the international political situation have made the international market economically volatile. However, the development of e-commerce has brought prosperity to China's CBEC business, which has become an important force in stabilising foreign trade and played an important role in stabilising global supply [1-3]. CBEC has become increasingly competitive, with international companies such as Amazon and Ebay, as well as domestic companies such as Jingdong and Tmall, entering the field [4-5]. In CBEC digital marketing, the application of cognitive decision-making (CDM) algorithms is of great value. Li et al. designed a hierarchical product classification and retrieval system suitable for CBEC shopping websites based on the analysis of image retrieval algorithms. The classification decision layer was used to determine the category of product images, and then the corresponding product image features were accurately retrieved. The recommendation results were highly accurate [6]. This algorithm is based on modeling the decision-making of individuals and exploring the theory and methods of how individuals make decisions under uncertainty. The study aims to explore the application of CDM algorithms in CBEC digital marketing to improve marketing effectiveness and economic efficiency. The study includes an introduction to CBEC digital marketing and CDM algorithms, a study of the pricing strategy problem in CBEC digital marketing, a test and analysis of the performance of the models and algorithms, as well as a summary and exposition of the study. The main contribution of the research is the application of CDM algorithms to CBEC digital marketing, which provides a new perspective in the field of international trade to improve marketing effectiveness and economic efficiency.

II. Related Works

CBEC and digital marketing have been hot topics in the economic field in recent years, and a large number of scholars have conducted research on them. Setkute et al. conducted research on digital marketing inapplicability in B2B small and medium-sized enterprises, and used qualitative research methods to investigate background factors of small B2B companies. They analyzed the obstacles that affect digital marketing practices, and the results showed that the "one size fits all" digital marketing mindset is not suitable for B2B small and medium-sized enterprises [7].

Yan et al. analyzed the impact of performance management systems on employee productivity in Chinese CBEC enterprises by using quantitative methods. Descriptive statistics were used as a data analysis tool to analyze the statistical data of 400 employees of the surveyed e-commerce enterprises using percentages and frequencies [8]. Li et al. conducted research on the impact of environmental regulation on CBEC exports of agricultural products. Based on the certification process of agricultural products under the influence of environmental regulation, they established an agricultural products output equation under the influence of environmental regulation, and analyzed how environmental regulation intensity affects the quality of agricultural products exported through CBEC and the competitiveness of agricultural products exporting enterprises [9]. CDM algorithms are based on modeling the decision-making process of individuals and exploring the theories and methods of how individuals make decisions under uncertainty. They are widely used in various fields. Ezaleden et al. used the NPSO algorithm to learn the importance of relationship types between concepts to complete a simulated recommendation system based on the highest ranking for dynamic learners. They studied the CLM and ECLM concept models, and the simulation results showed that ECLM performed better than other existing methods, with a mean reciprocity rate value of 0.780 [10].

Cao et al., to achieve intelligent recognition of surface Electromyography (sEMG) gesture signals in human-computer interaction, proposed a sEMG gesture recognition intelligent model combined with feature extraction, genetic algorithm (GA) and SVM model, and proposed adaptive mutation particle swarm optimization (AMPSO) algorithm to optimize SVM parameters. Research outcomes denoted that AMPSO-SVM could effectively recognize low-frequency sEMG signals of different gestures, with good performance [11]. Stojanovic Blaza et al. applied intelligent optimization algorithms to stability control of multi machine power systems. The stability of this method in system dynamic stability control has been demonstrated through comparative experiments of simulation results [12]. Jarndal et al. applied PSO and GA intelligence optimization algorithms to the efficient electrothermal large signal GaN HEMT modeling. Experiments have shown that the model also exhibited accurate simulation of nonlinear power amplifiers, with excellent computational speed and convergence [13]. Song et al. coupled the temperature and structure of the braking system using finite element method, and used GA parameter optimization and sensitivity analysis. Experiments have shown that this method can optimize the thermal stress and deformation problems of fan openings in high-temperature environments [14].

In summary, although researchers have conducted extensive research on various aspects of CBEC and digital marketing, research in digital marketing decision-making is still very scarce, which is highly related to CBEC profits. Using CDM algorithms to conduct due research on it has high potential application value.

III. Design of CBEC Digital Marketing Pricing Decision Model

With digital marketing as the support, the digital marketing manages the production, logistics, distribution, publicity and a series of enterprise marketing activities that run through the product cycle online and offline. The marketing channel tends to be flat, and the direct communication between enterprises and consumers will cost business operations. Product pricing is the basic point of digital marketing and the main factor for scholars to analyze enterprise marketing decisions. At present, the research on product pricing decisions focuses on the two-stage sales model of “pre-sale+sales”, and the research will also study the digital marketing pricing under this sales model.

A. *Design of Product Pricing Model for the Diffusion Benefits of Cross-border e-commerce Digital Marketing*

The research on product pricing focuses on the game and equilibrium between consumer behaviour and enterprises' pricing. In the two-stage sales model of “pre-sale+sales”, it is mainly the impact of enterprises' pricing diffusion on the demand of the later market. The pattern of this diffusion event is shown in Fig. 1.

TABLE I. VARIABLE SYMBOLS

Symbol	Meaning; implication; sense; import; meanings
c	The production cost for each product sold
p_1	Pre-sale price
p_2	Sales period price
N	Number of consumers receiving product information (i =1,2)
u	Utility values obtained per unit of product
θ	Strategic consumers in the pre-sale period of the proportion (0< θ <1)
Δ	Utility values obtained by product diffusion
Q	Order quantity of products
m	Regret utility
δ	The possibility that consumers will buy a product during the normal sales period
D_1	Product demand during the pre-sale period
D_2	Crystal production demand during the sales period
Π_1	Product profit during the pre-sale period
Π_2	Crystalline production profit during the sales period.
β_1	The effect coefficient of the innovation effect, ($\beta_1 > 0$)
β_2	The influence coefficient of the imitation effect, ($\beta_2 < 0$)
β_w	Integrated imitation effect coefficient
η	Scale effect coefficient
$F(.)$	The probability of consumers buying a product during the pre-sale period.
N_{D1}	The number of consumers attracted by the product diffusion effect
g_r	Out of stock cost of unit product due to out of stock
$k(.)$	The impact of crystal production diffusion on retailers' normal sales period demand
φ	The percentage of negative word of mouth

In the pre-sale stage of products, CBEC publishes information such as pre-sale and normal sales prices, and quantities on e-commerce platforms. To attract consumers to purchase, CBEC sets pre-sale prices lower than normal sales prices. However, due to the limitations of information dissemination on e-commerce platforms, it is not possible for all consumers to receive pre-sale related information. Only some well-informed consumers can successfully receive product pre-sale information, while consumers who have not received product pre-sale information are classified as message blocking consumers. Informed consumers judge the effectiveness of products based on product information, measure prices and demand, and make decisions. Consumers who purchase products publish their usage experiences on the internet, and over time, their word-of-mouth (WoM) accumulates or decreases, leading to the diffusion of product information. This diffusion effect affects the number of consumers attracted during the normal sales phase [15-16]. The diffusion model of Base is shown in Fig. 2.

The process of converting potential purchasing groups is influenced by two aspects: innovation and imitation effects. Innovation effect mainly refers to the influence of external factors such as advertising, marketing, and price on shopping behavior, while imitation effect is influenced by WoM to cause potential groups to follow the buying behavior. When product diffusion events occur, CBEC enterprises make decisions on product supply based on factors such as reputation and the number of pre-sale consumers in the product diffusion effect, to minimize cross-border logistics storage costs and achieve max profits. Because the product diffusion effect will affect the actual demand in the pre-sale+sales period, the optimal pricing decisions for enterprises to obtain max profits are divided into pre-sale and sales price decisions. The variable symbols used in the decision model are displayed in Table I.

Under the diffusion effect, the optimal selling price decision of a product can be expressed as Eq. (1).

$$p_2^* = \begin{cases} \dfrac{\lambda + \theta\lambda \bar{F}(p_2) + N_{D1}}{\theta\lambda f(p_2)}, & N_{D1} \le Q - 2\lambda \\ \dfrac{Q - (1-\theta)\lambda - \theta\lambda F(p_2)}{\theta\lambda f(p_2)}, & N_{D1} > Q - 2\lambda \end{cases} \tag{1}$$

In Eq. (1), $\bar{F}(p_2) = 1 - F(p_2)$ denotes the proportion of consumers who purchase products during the sales period. It should be noted that there is a situation where $\min(Q - (1-\theta)\lambda - \theta\lambda F(p_2), \theta\lambda\bar{F}(p_2) + \lambda + N_{D1})$ is taken. When supply exceeds demand, i.e. $N_{D1} \le Q - 2\lambda$, the sales profit of CBEC is as expressed in Eq. (2).

$$\begin{aligned} E(\Pi_2) = {} & p_2(\lambda + \theta\lambda\bar{F}(p_2) + N_{D1}) \\ & - c(Q - (1-\theta)\lambda - \theta\lambda f(p_2)) \end{aligned} \tag{2}$$

If the second-order derivative is less than 0, then the profit function has an optimal sales period price. When demand exceeds supply, there is $N_{D1} > Q - 2\lambda$. Since $\bar{F}(p_2) = 1 - F(p_2)$ is a decreasing function of p_2, the optimal sales period price relationship is shown in Eq. (3).

$$\begin{aligned} E(\Pi_2') = {} & (p_2 - c)(Q - (1-\theta)\lambda - \theta\lambda F(p_2)) \\ & - g_r(2\lambda + N_{D1} - Q) \end{aligned} \tag{3}$$

From Eq. (3), it is easy to obtain that its second-order derivative is less than 0, and the function has the optimal sales period price. From the above analysis, the product price decision during the sales period of CBEC mainly depends on the impact of diffusion effects on consumer demand. When the impact is small, there is still surplus in the product, and the sales price will increase with the increase of diffusion. On the contrary, if the product supply is insufficient, the setting of sales prices can temporarily ignore the diffusion effect of the product during the pre-sale period. The expression for the optimal pre-sale price of a product under the diffusion effect is shown in Eq. (4).

$$\begin{aligned} p_1^* &= u - (u - p_2^* + \Delta)\delta + m(1-\delta) \\ &= (1-\delta)(u+m) + (p_2^* - \Delta) \end{aligned} \tag{4}$$

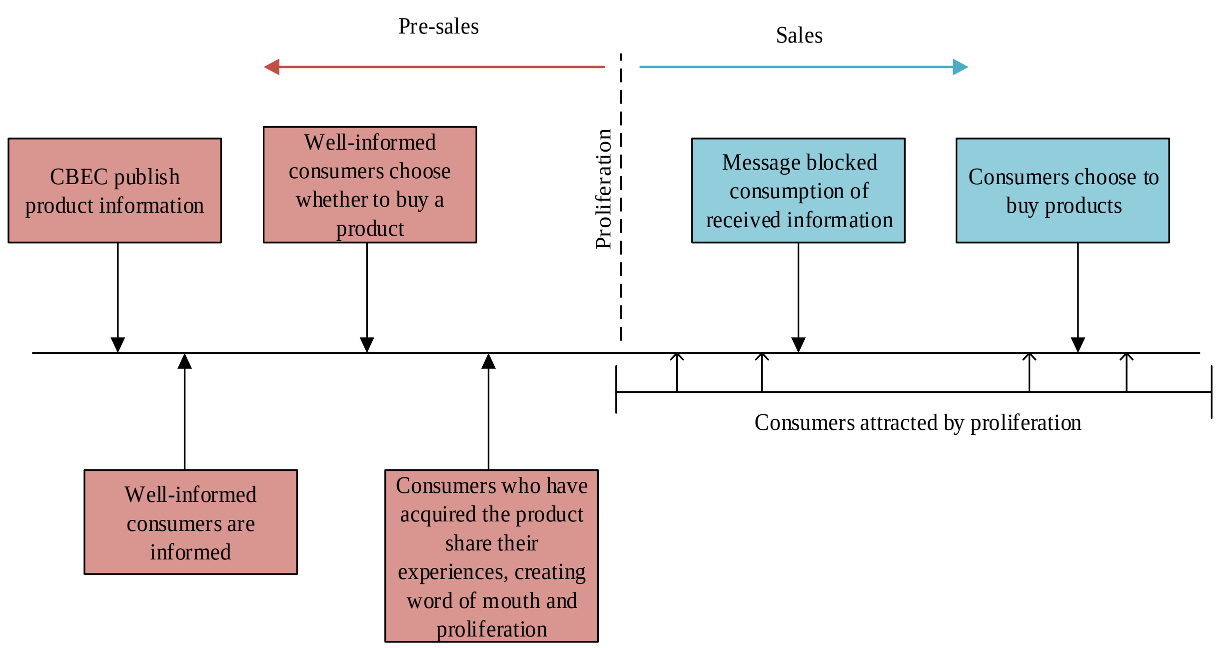
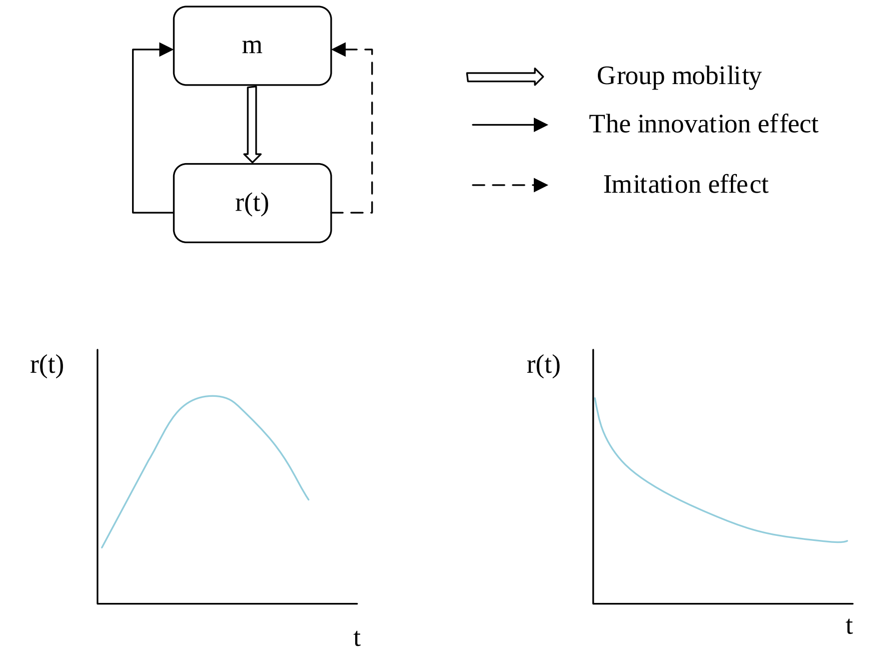


Fig. 1. Event diffusion model.



(a) The imitation factor is greater than the innovation factor

(b) The innovation factor is greater than the imitation factor

Fig. 2. Base diffusion model.

The pre-sale pricing of CBEC is influenced by the sales period price. As the diffusion effect increases on consumer demand, when supply exceeds demand, the sales price increases accordingly. The pre-sale price is higher, but when supply is less than demand, it has little impact on the pre-sale price. The scale effect of WoM refers to the impact of WoM generated by the sale of a product on the purchasing intention of potential consumers, increasing (or decreasing) the inflow of intended consumers, and the potential consumers who form the scale effect of WoM are ηN_2. Consumers who purchase products will be divided into positive and negative WoM groups, which is known as the WoM ratio effect. A product pricing model that combines the scale and proportion of WoM to form a dual WoM diffusion effect. The impact of product diffusion on the normal sales period demand of CBEC in the model is shown in Eq. (5).

$$\begin{aligned} k(D_1) = \beta_1 + \beta_2 + \frac{\varphi((1-\theta)N_1 + \theta\lambda F(p_2))}{\eta N_2} \\ -\beta_2 - \frac{\varphi((1-\varphi)(1-\theta)N_1 + \theta N_1 F(p_2))}{\eta N_2} \end{aligned} \tag{5}$$

In Eq. (5), β_1 and β_2 denote the coefficients of innovation and imitation effects, respectively. The coefficient of innovation effect refers to the coefficient of external factors other than WoM that affect consumer shopping behavior. The coefficient of imitation effect stands for the coefficient of shopping behavior affected by WoM transmission, which is divided into positive WoM imitation effect coefficient β_{2+} and negative WoM imitation effect coefficient β_{2-}. The comprehensive imitation effect coefficient of the two is denoted in Eq. (6).

$$\beta_w = (1-\varphi)\beta_{2+} - \varphi\beta_{2-} \tag{6}$$

Under the dual WoM diffusion effect, the impact of WoM diffusion on customer demand during CBEC sales is shown in Eq. (7).

$$k(D_1) = \beta_1 + \beta_w \frac{(1-\theta+\theta F(p_2))}{\eta} \tag{7}$$

The dual effects of WoM and diffusion effects jointly constitute the consideration factors for CBEC pricing decisions, considering multiple supply and demand relationships. Under the influence of the dual WoM diffusion effect, the sales price can be calculated as expressed in Eq. (8).

$$p_2^{**} = \begin{cases} \dfrac{(1+\theta+\beta_1) + \dfrac{\beta_w}{\eta}(1-\theta)(1+F(p_2)) + c\theta f(p_2)}{\theta f(p_2) - \dfrac{\beta_w}{\eta}\theta f(p_2)}, \\ \dfrac{Q}{\lambda} - 2 \geq \beta_1 + \dfrac{\beta_w}{\eta}(1-\theta+\theta F(p_2)) \\ \dfrac{Q-(1-\theta)\lambda-\theta\lambda F(p_2)}{\theta\lambda f(p_2)} + c + g_r(1-\dfrac{\beta_w}{\eta}), \\ \dfrac{Q}{\lambda} - 2 < \beta_1 + \dfrac{\beta_w}{\eta}(1-\theta+\theta F(p_2)) \end{cases} \tag{8}$$

According to Eq. (8), when supply exceeds demand, p_2^{**} is positively correlated with β_1, and is influenced by β_w and η. That is, the higher the external influence of WoM on consumers, the greater the diffusion effect. At this point, a high pricing decision can be chosen. When supply and demand are not met, the sales price is highly correlated with the existing reputation of the product. Therefore, the premise for the optimal pricing of CBEC is as Eq. (9).

$$p > c + g_r(1 - \frac{\beta_w}{\eta}) \tag{9}$$

Under the dual WoM diffusion effect, the pre-sale price of the product is set as shown in Eq. (10).

$$p_1^{**} = u - (u - p_2^{**} + \Delta)\delta + m(1-\delta) \tag{10}$$

In summary, the pricing of products during the pre-sale period of CBEC is influenced by the dual WoM diffusion effect. When the supply is sufficient, the increase in innovation effect has a significant impact on potential consumers, and the pre-sale price is higher. The product diffusion effect is influenced by comprehensive WoM, which also affects product pricing. When supply does not meet demand, pricing is only related to WoM.

B. CD-ABC Algorithm Design Based on Security Domain Search Strategy and Information Diffusion Statistical Model

The products and markets in CBEC activities are relatively complex, requiring a deep understanding of consumer behavior and preferences to make better decisions. There is a high demand for the global optimization ability of CDM algorithms. Therefore, an artificial bee colony (ABC) algorithm with strong global optimization ability, high solving accuracy, and few control parameters is selected to solve the pricing decision problem. The ABC algorithm is derived from human observation of the information exchange process during bee foraging. Karaboga proposed the ABC algorithm based on this process, dividing individuals searching for the target space into three roles: picking bees, observing bees, and reconnaissance bees. These three roles switch to each other as needed. Picking bees search for new foraging locations based on known information and share it with observing bees. Reconnaissance bees are responsible for randomly searching for new honey sources near the hive. In the ABC algorithm, the dimension of the solution to the optimization problem is D dimension, and one solution of the problem is the coordinate corresponding to a honey. The amount of honey is the fitness of the solution, and the number of honey and bees collected or observed is equal, set as SN. The process of searching for the next honey position is as shown in Eq. (11) when the bees reach one honey position [17-20].

$$x_{id} = x_{id} + \varphi_{id}(x_{id} - x_{kd}) \tag{11}$$

In Eq. (11), $i = 1, 2, \cdots, SN$, $d = 1, 2, \cdots, D$, and φ_{id} are random numbers of [-1.1], and $k \neq i$. After picking bees to find new honey, it compares the new honey position with the original honey position, and retains the position with the highest amount of honey. If the new honey quantity is lower than the old honey, the information is transmitted to the observing bee [21]. It observes the bees and calculates the probability of the next honey occurrence position based on Eq. (12).

$$p_i = \frac{fit_i}{\sum_{j=1}^{SN} fit_j} \tag{12}$$

Picking and observing bees will traverse the honey in the current domain. If the fitness value of the honey does not improve before reaching the limited number of iterations, the honey will be discarded. At the same time, the bees in this position will be transformed into reconnaissance bees, and the fit_i in the equation represents the fitness value of the solution. After the process is completed, the reconnaissance bee will search for the next honey in the solution space, as shown in Eq. (13).

$$x_{id} = x_d^{\min} + r(x_d^{\max} - x_d^{\min}) \tag{13}$$

In Eq. (13), $x_d^{\max}$ and $x_d^{\min}$ denote the upper and lower limits of the D-dimensional solution space, and r means a random number in the interval [0,1]. The reconnaissance bee searches in the solution space by randomly selecting a number in the D-dimensional solution space to obtain a location. The ABC algorithm flow is shown in Fig. 3.

The ABC algorithm starts by randomly initializing the bee colony, calculating the amount of honey at the location where the bees are collected, and then the bees start searching for the next honey to update the honey location. At the same time, the bees select the honey location for observation. To ensure that bees are not attacked (interfered) by other groups when searching for new honey sources, a security domain search strategy is studied, as shown in Eq. (14).

$$v_{id} = x_{id} + r(x_{id} - x_{kd}) + r(SP_d - x_{id}) \tag{14}$$

In Eq. (14), SP_d indicates the safe location of the d honey source. Obviously, v_{id} is randomly guided from multiple directions and approaches the safe location. The safe location in the group is expressed in Fig. 4.

In a bee colony, the area where the proportion of bees to the population is greater than μ is considered a safe area. The triangle in the figure represents bees, and the circle centered around the safe position C_d is considered a safe area. The maximum safe distance of the $C_j = SP = (SP_1, SP_2, \cdots, SP_D)$ safe area is the radius MSD of SP. In the observing bee search stage, it conducts probability selection according to the honey source information transmitted by the picking bee to find the optimal location for mining. However, this method is uncertain and blind, and cannot ensure that good honey sources are more attractive to observing bees than poor honey sources. The statistical model of information diffusion is introduced to adjust the selection strategy of the picking bee, as shown in Eq. (15).

$$p(x_i) = \frac{1}{(N-1)\sqrt{2\pi}} e^{\frac{-(fit(x_i) - fit_{\max})^2}{2h^2}} \tag{15}$$

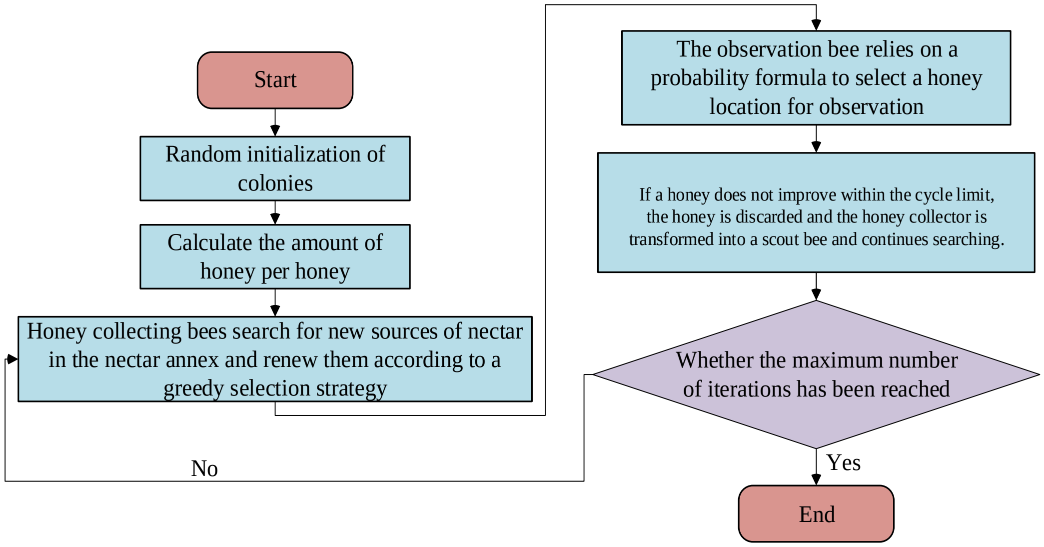


Fig. 3. ABC algorithm flowchart.

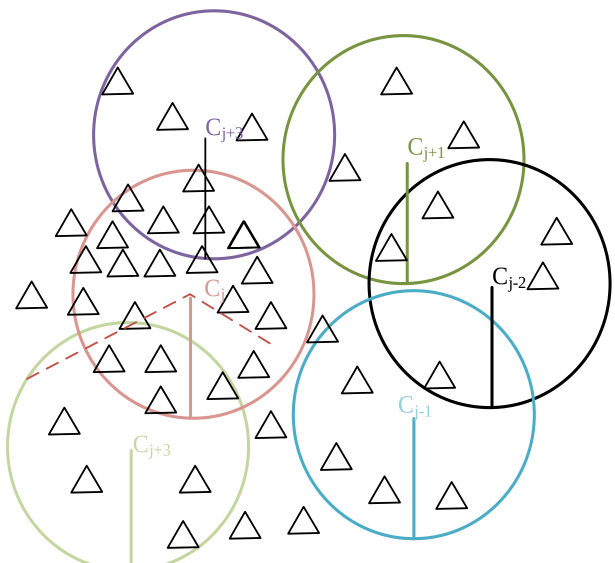


Fig. 4. Safe location in a group.

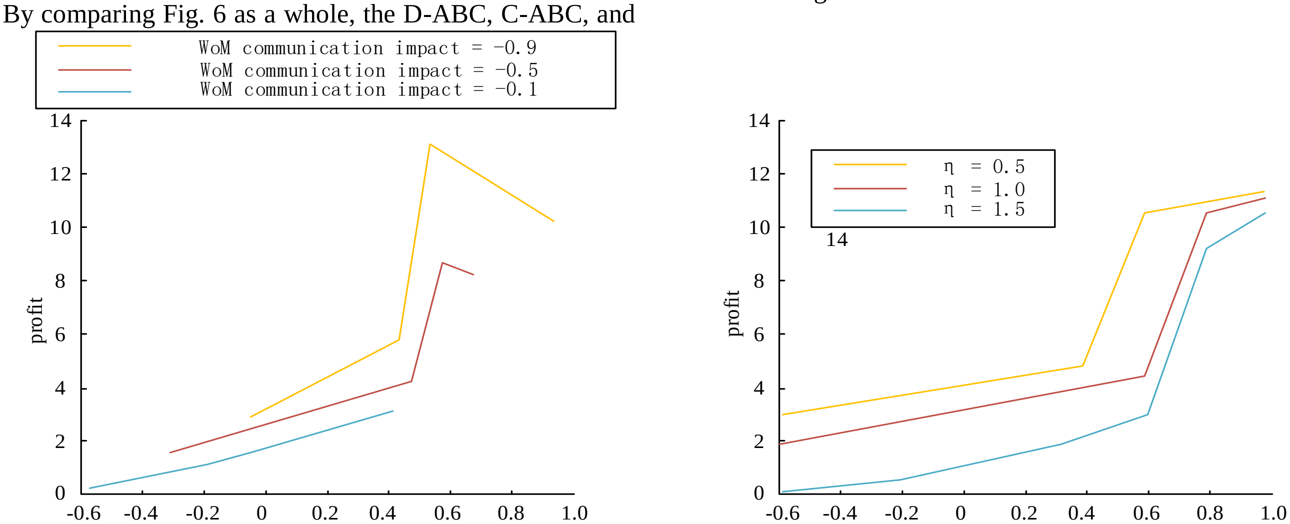
In Eq. (15), $p(x_i)$ refers to the probability of observing bees selecting honey source i, and h stands for the information diffusion coefficient.

IV. Performance Test of CBEC Digital Marketing Pricing Decision Model

Based on research on CBEC products, a clothing product of a certain CBEC enterprise was selected as an example for model performance testing. First, the relationship between innovation effect coefficient and pre-sale pricing under different WoM propagation of product pricing model, and the relationship between comprehensive imitation coefficient and CBEC pricing under different word of mouth scale were analyzed. The impact of product diffusion effect and comprehensive imitation effect on CBEC profits was investigated. The results are shown in Fig. 5.

As shown in Fig. 5, Fig. 5(a) and Fig. 5(b) show the impact of product diffusion effect and comprehensive imitation coefficient on CBEC profits, respectively. Fig. 5(a) shows that the impact of WoM communication has increased, and the profits obtained by CBEC have increased. At the same time, as the product diffusion effect increased, the profits obtained by CBEC continued to increase. Observing the diffusion effect coefficient of products, as the effect coefficient increased, supply exceeded demand, sales decision prices increased, and pre-sale prices were higher. At this time, CBEC profits increased. When supply did not meet demand, the increase in diffusion effect only increased the gap in goods, leading to a decrease in CBEC profits. Fig. 5(b) shows the impact of WoM scale effect on CBEC profits under the dual WoM diffusion effect. As the WoM scale coefficient increased, the amount of potential consumer conversions increased, and the optimal profits obtained by CBEC increased. As the comprehensive imitation coefficient increased, the diffusion effect of products increased and CBEC profits increased due to the influence of WoM scale effect. The rationality of the model was verified. Based on this, the CD-ABC algorithm's wide area search capability and resource utilization capability were tested to verify the excellent performance of the algorithm. The C-ABC algorithm (secure neighborhood search ABC algorithm), D-ABC algorithm (information diffusion ABC algorithm) and ABC algorithm were used as comparison objects. Twenty tests were conducted on 22 benchmark functions (D=30). The population setting was 30, $\lim it = 200$, and the maximum number of iterations was 100000. The test results are shown in Fig. 6.

By comparing Fig. 6 as a whole, the D-ABC, C-ABC, and CD-ABC algorithms generally outperformed the ABC algorithm in most functions. In most functions, the convergence degree of the D-ABC and C-ABC algorithms was better than that of ABC, indicating that compared to traditional ABC algorithms, the two improved methods proposed in the study had good performance optimization. CD-ABC algorithm had better performance than C-ABC and D-ABC algorithms in most functions, and its rate of convergence was significantly faster than D-ABC and C-ABC, indicating the effectiveness of the improved CD-ABC algorithm. To further illustrate the advantages of information diffusion probability over ABC probability, a test was conducted on the impact of bees on the honey source search probability for the same initial population. The results are shown in Fig. 7.



(a)The impact of product diffusion effects on the profitability of CBEC

(b)The impact of the combined imitation factor on CBEC profits

Fig. 5. The impact of product diffusion effects and combined imitation effects on the profitability of CBEC.

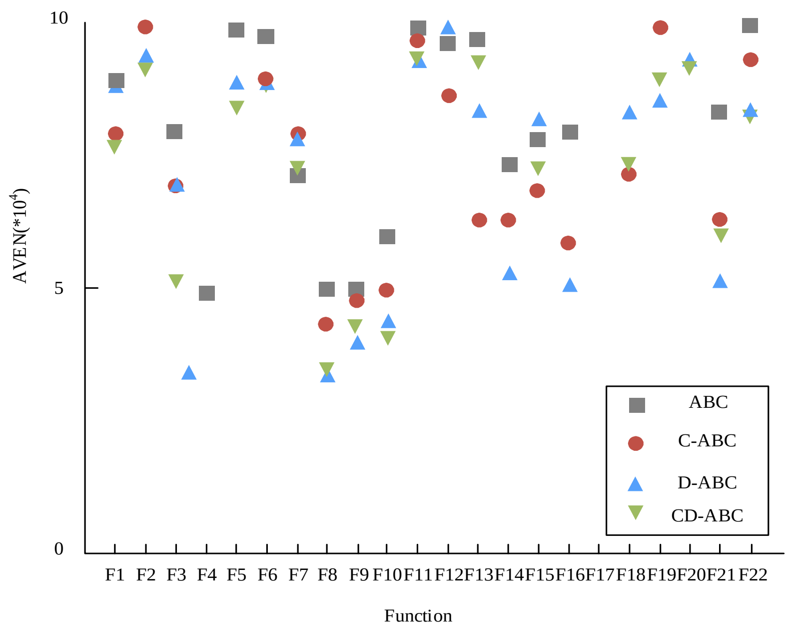
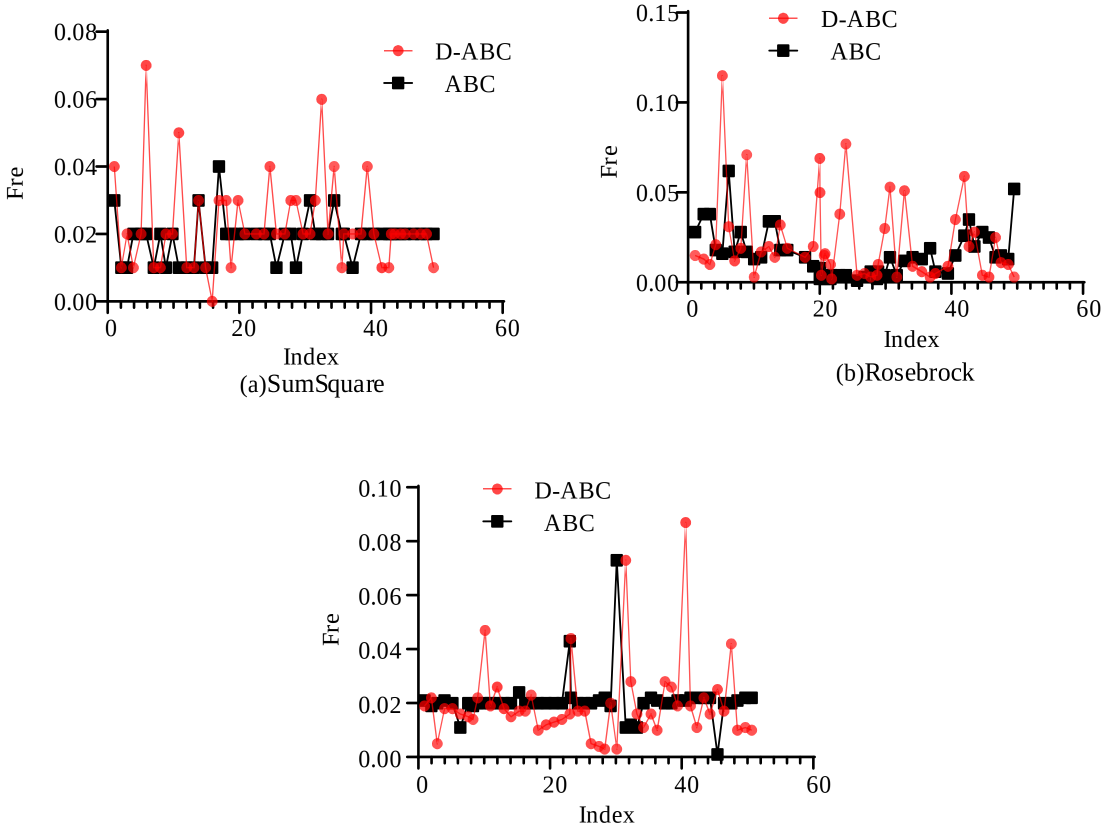


Fig. 6. Algorithm average AVEN comparison.



(a)SumSquare

(b)Rosebrock

(c)Ackley

Fig. 7. Individual evolution frequency test.

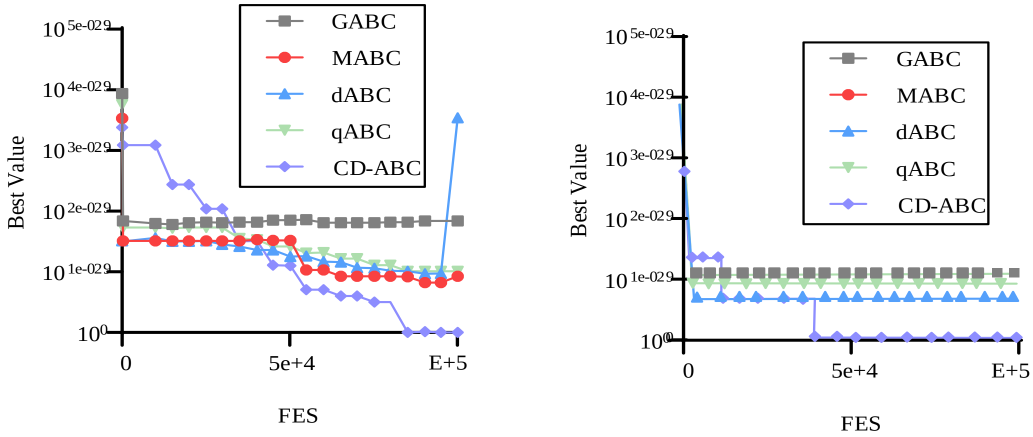
As shown in Fig. 7, representative unimodal functions SumSquare, uncertainty function Roserock, and multimodal function Ackley were selected for experiments to test the ABC algorithm's concept. Comparing Fig. 7 as a whole, there was no significant difference in the individual evolution frequency of the ABC algorithm, indicating that it was unable to detect the superiority of honey sources. However, in D-ABC, some individuals exhibited higher evolution frequencies, indicating that the information diffusion probability could detect the superiority of honey sources and convey it to the observation bees, so that the excellent and beautiful honey sources received more attention. This indicated that the information diffusion probability could detect the value of hidden honey sources in ABC, improving ABC's deep mining ability. Based on the above test results, the CD-ABC algorithm was compared and tested with other ABC variant algorithms with excellent improvement effects. The parameter settings and algorithm are displayed in Table II.

to conduct a fair comparison test on the above improved algorithms, the same parameter settings were used for the experiment. The results of the algorithm rate of convergence comparison test are shown in Fig. 8.

When D is set to 30, the CD-ABC algorithm outperformed GABC, MABC, qABC, and dABC in 14 functions. Fig. 8 shows the convergence curves of the above algorithms on some functions. CD-ABC showed high efficiency and Rate of convergence in most functions. Based on the above verification of the efficient performance of CD-ABC, its performance in solving practical pricing problems was tested. The product pricing model with dual WoM diffusion effect proposed in the study was used for solution analysis, and compared with particle swarm optimization (PSO), whale optimization algorithm (WOA), GA, ABC and WOA-GA algorithms. The experimental object was the pricing of clothing products in CBEC, as shown in Fig. 9.

TABLE II. ALGORITHM COMPARISON TEST PARAMETER SETTINGS

Improved algorithms	Parameter settings		
	N	limit	C/P/r/u
GABC	50	200	1.5
MABC	50	200	0.7
dABC	50	200	/
qABC	50	200	1.5
CD-ABC	50	200	0.3



(a)Sphere (a)Elliptic

Fig. 8. Comparison test results of algorithm rate of convergence.

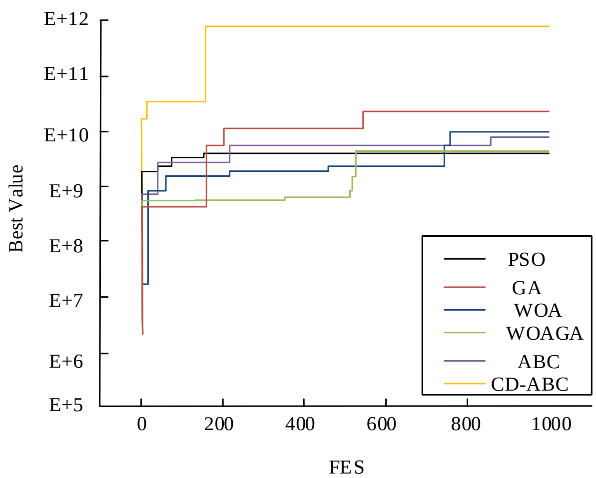


Fig. 9. Iterative curves for solving clothing pricing problems using different algorithms.

Fig. 9 shows the iteration curve of each algorithm to solve the CBEC clothing pricing problem under the dual WoM diffusion effect model. The CD-ABC algorithm obtained the optimal pricing decision, and its rate of convergence was fast. After 200 iterations, the convergence was completed, and the number of iterations was far lower than the common decision solving algorithm. And the pricing optimization decision obtained by the algorithm resulted in CBEC gained much higher profits than other algorithms, ultimately benefiting 7.95e+11. The comprehensive imitation effect calculated by the CD-ABC algorithm in 200 iterations was -0.14, the reputation scale effect was 1.34, the pre-sale price was finally set at 347.49, and the sales price was 641.393, which indicated that the pricing obtained by the CD-ABC algorithm was closer to life and could provide a reference for enterprises to make pricing decisions. To demonstrate the applicability of the CD-ABC algorithm in solving pricing decision-making problems in various application scenarios, a CBEC enterprise's electronic product was selected as a case for comparative testing. The test results are shown in Fig. 10.

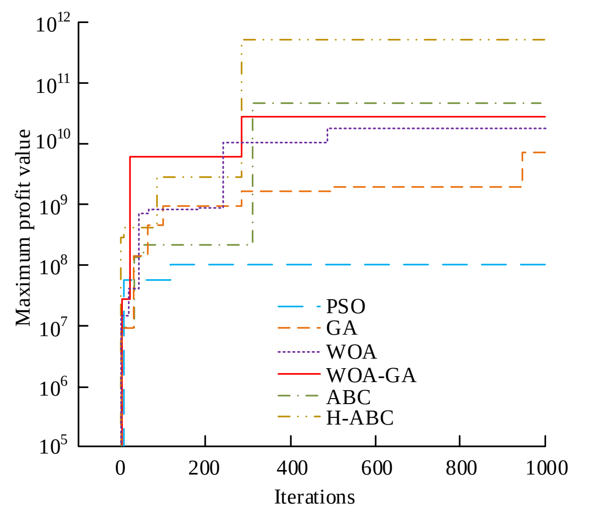


Fig. 10. Iterative curve for solving the pricing problem of cross border e-commerce electronic products.

Fig. 10 shows the iteration curve of each algorithm to solve the pricing problem of CBEC electronic products under the dual WoM diffusion product pricing model. The CD-ABC algorithm obtained the maximum profit. After 230 iterations, the optimal profit decision reached 5.31e+11, which was far higher than the results of other algorithms. However, its rate of convergence was worse than that of GA, and its global optimization ability was weak. However, overall, it still had high performance in solving CBEC pricing problems, which could provide a certain basis for CBEC pricing decisions.

V. CONCLUSION

To optimize CBEC marketing strategies and improve competitiveness, the research focused on the pricing throughout the whole e-commerce marketing, built a dual WoM diffusion product pricing model suitable for CBEC product pricing, and optimized the traditional ABC algorithm to enable it to have excellent performance in solving the dual WoM diffusion product pricing model strategy. The performance test outcomes of the model indicated that the impact of WoM communication increased, and the profits obtained by CBEC increased. At the same time, as the product diffusion effect increased, the profits obtained by CBEC continued to increase. Under the dual WoM diffusion effect, the impact of WoM scale effect on CBEC profits increased with the coefficient of WoM scale, the number of potential consumer conversions, and the optimal profits obtained by CBEC. Using the C-ABC, D-ABC and ABC algorithms as comparison objects, the test results of 22 benchmark functions showed that the D-ABC, C-ABC and CD-ABC algorithms generally outperformed ABC algorithm in most functions, and the convergence degree of D-ABC and C-ABC algorithms was better than ABC algorithm. This is because the C-ABC and D-ABC algorithms introduced security-specific domain search strategies and information diffusion probabilistic model optimisation mechanisms that are more suitable for dealing with complex non-linear problems in solving the dual WoM diffusion product pricing problem. In particular, the CD-ABC algorithm, by combining the advantages of C-ABC and D-ABC, was able to adjust the search strategy more quickly, avoid premature convergence, and maintain a balance between exploration and exploitation. This allowed the algorithm to find solutions closer to the global optimum even when faced with the interaction of multiple factors in a changing market environment. For the same initial population, the test results of observing the influence of bees on the honey source search probability showed that some individuals in D-ABC had a high evolutionary frequency. When D was set to 30, the CD-ABC algorithm performed better than GABC, MABC, qABC, and dABC in 14 functions. In most functions, the CD-ABC showed efficient solution efficiency and rate of convergence. This is due to the efficient evolutionary strategy of the CD-ABC algorithm in dealing with the colony's search behaviour for nectar sources. In the D-ABC algorithm, individuals exhibited different evolutionary frequencies, and this differentiated evolutionary strategy provided more diverse search paths for the probabilistic model of information diffusion. When the evolution frequency parameter was set to 30, the CD-ABC algorithm was able to adjust its search strategy more accurately, which ensured excellent performance on various test functions, especially in comparison with other state-of-the-art algorithms such as GABC and MABC. This diversified search path not only accelerated the convergence speed but also improved the solution efficiency, enabling the CD-ABC algorithm to efficiently approximate the global optimal solution in complex optimisation problems, especially when simulating market decisions in real-world dynamic environments. The actual strategy solution findings showed that in the CBEC clothing pricing problem, the CD-ABC algorithm converged after 200 iterations, with lower iterations than common decision solving algorithms and much higher benefits than common algorithms, reaching 7.95e+11. The comprehensive imitation effect was -0.14, the WoM scale effect was 1.34, the pre-sale price was ultimately set at 347.49, and the sales price was 641.393. When solving the pricing problem of CBEC electronic products, after 230 iterations to reach convergence, the optimal profit decision obtained reached 5.31e+11, which was much higher than the results obtained by other algorithms. The research proposed a dual WoM diffusion product pricing model and the CD-ABC algorithm, which had better computational performance compared to common models in CBEC pricing decision-making problems. However, their lack of consideration for the background of the interaction of multiple factors in practical problems is also an area for further research to improve.

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