Research on e-Commerce Distribution Optimization of Rice Agricultural Products Based on Consumer Satisfaction

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ABSTRACT With the continuous development of agricultural product e-commerce platforms and the rapid growth of trading volume, conducting in-depth mining and analysis of online review data to improve consumer satisfaction is of considerable importance. This paper uses JingDong's self-run online reviews of rice agricultural products as the research object and analyzes the logistics factors that affect consumer satisfaction through text mining technology. A multi-objective model for logistics center distribution path optimization under a soft time window was constructed. The model used the results of online review analysis, namely, packaging integrity, delivery timeliness, and logistics cost, as the goals, and the model used ant colony algorithm (ACO) and genetic algorithm (GA) to solve the optimal distribution solution to minimize the penalty cost and transportation cost. Through examples to solve the optimal distribution vehicle number and shipping routes, in addition, a comparison of the two types of algorithm performance of the model under different node number indicated that the number of nodes affects algorithm performance. With a node number below 50, the ant ACO has high precision and a better distribution path. With a node number above 50, GA has more comprehensive performance. The average efficiency of the GA is 12.28% higher than that of ACO.

INDEX TERMS Consumer satisfaction, logistics distribution, soft time window, ant colony algorithm, genetic algorithm.

I. INTRODUCTION

The single yield of rice in China has increased annually in recent years, precluding the completion of rapid sales of rice agricultural products during the preservation period by relying on traditional offline transactions. Therefore, merchants use e-commerce platforms to expand the sales channels of agricultural products. Most merchants spend considerable amounts of money to hire celebrities to represent them and carry out discount activities to attract consumers' attention to increase sales. However, these merchants ignore the most basic demands of consumers, that is, by improving consumer satisfaction, which is the most effective way to ensure the increase in product sales.

According to statistics, China's rural online retail sales have maintained a rapid growth since 2015, with an increase

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of 1.44 trillion yuan in six years. In 2020, the total retail sales will reach 1.79 trillion yuan, and about 60% of Chinese people live on rice as the staple food, so the online trading market of rice agricultural products has a huge scale and huge development potential in the future. However, many factors affect the development of e-commerce of rice agricultural products, which can be mainly divided into two aspects. The first aspect is the lack of consumer participation. Most e-commerce companies do not recognize the importance of consumers, resulting in consumer distrust and dissatisfaction with e-commerce. Hasan Beyari studied consumer satisfaction among 372 students in Australia and Saudi Arabia by means of a questionnaire survey. The results showed that trust is the biggest dimension that affects consumer satisfaction [1], indicating that if e-commerce fails to take consumers' wishes into full consideration, it will not be trusted by consumers. This deficiency seriously restricts the development of e-commerce. Second, the logistics system is not

perfect, and problems affecting product quality such as long delivery time and damaged packaging should be avoided. The storage mode must be optimized to adapt to rice commodities of different standards. The construction of a logistics system also affects the rapid development of rice agricultural e-commerce [2].

A longstanding challenge in logistics enterprises is how to ensure that agricultural products are not problems of corrosion rate. Therefore, many scholars study the transportation of agricultural products from different sides, Jarupan, L et al studied the potential of oil palm leaf fiber materials for protective packaging under wet conditions through mechanical and physical properties of packaging materials [3]. Duin, Jhr Van *et al.* used historical distribution data to predict future distribution results and applied multiple linear regression technology to the development, identification, and prediction of accurate addresses within a region. Currently, this technology has been successfully applied in a logistics enterprise to ensure the accurate delivery of goods in the distribution process [4]. Combined with the concept of sustainable development of green logistics, Su and Fan studied the green vehicle routing problem based on traffic flow by controlling costs, improving energy efficiency, reducing carbon emissions and improving customer satisfaction [5]. Some scholars investigated the direction of transportation equipment and logistics mode, but these studies are auxiliary work, and the fundamental problem remains the delivery speed. How to understand consumer needs through data resources and complete distribution from the perspective of consumer satisfaction is the future development direction of agricultural logistics enterprises.

For customer satisfaction research, Justin Paul *et al.*, through using a questionnaire on customer satisfaction factors, found that the degree of word of mouth, staff quality, shopping environment, economics, family shopping, and shopping deals are six factors that have a significant influence on customer satisfaction and guide store development [6]. Based on Dempster-Shafer's (D-S) evidence theory for measuring hotel customer satisfaction, the reliability of online review information from multiple online travel review sites was analyzed. According to the customer satisfaction ranking to develop customer satisfaction improvement strategy, to help the hotel managers understand the hotel customer satisfaction, and formulate the corresponding improvement strategy, so as to enhance the hotel competitiveness [7]. On the basis of the perspective of use and satisfaction theory, Alnawas *et al.* studied the data obtained from seven large shopping malls in the form of questionnaires and confirmed a significant positive relationship between consumers' purchase intention and consumer satisfaction [8]. Medina-Merodio's proposed system provides a customer vision for the organization that makes possible the implementation of customer-retention initiatives that increase customer satisfaction [9]. Handayani et al used the customer satisfaction index and importance–performance analysis to determine the satisfaction of consumers and propose reasonable suggestions for

scenic spots to promote the development of rice agricultural tourism in wetlands [10]. Brandtner, P. *et al.* studied Austria's five big retail chains to assess the effect of COVID-19 on consumer satisfaction, finding that consumer satisfaction was generally significantly reduced. In addition, through the mining of online reviews, they found that store facility layout, product availability, and waiting time in shopping were three factors that had a considerable effect on customer satisfaction. Their research provides a basis for a comprehensive and reasonable discussion of the impact of COVID-19 on consumer satisfaction and cognition [11]. At present, studies on consumer satisfaction mainly focus on industries such as tourism, hotels, and catering. Few scholars have linked consumer satisfaction with rice agricultural product sales, leading to the lack of theoretical guidance for e-commerce of rice agricultural products.

Text mining can directly obtain the unknown value information hidden inside a text and can extract political, commercial, cultural, and other information from complex text through methods such as viewpoint mining and sentiment analysis [12]–[14]. Compared with questionnaires and interviews, the information obtained by text mining is more authentic and objective and is not affected by the subjective will of the sender [15]. As regards research on text mining of online reviews, Zhao YB *et al.* believe that online reviews have commercial value in the era of big data, and through the analysis of hotel review samples, they find that online reviews can provide higher levels of insight and more diversified suggestions, and reasonable use of electronic word of mouth can improve hotel efficiency [16]. Jaewon Choi *et al.* extracted and identified keywords affecting organic product sales by using the potential Dirichlet distribution method and found that packaging design, food quality, distribution risk, freshness, and source risk are important online factors influencing consumers to buy organic products [17]. Robert Campbell *et al.* used a two-stage investigation to identify factors affecting sustainable local food production and distribution systems. In the first stage, local residents and international students were surveyed to determine their attitudes and values about shopping at farmers' markets and buying local goods. In the second stage, text-mining techniques were used to obtain data on Twitter that measured consumer feedback on food-buying activities. The analysis results show that the two main factors influencing the purchasing decision of local agricultural products are food attributes and supporting community economic development [18]. Although text mining technology is relatively mature, it is only widely used in fields such as tourism, hotels, and film evaluation, and relatively few studies have been conducted in the field of rice agricultural product sales.

Solving logistics centers and distribution with time constraints is an expansion of the traditional vehicle routing problem (VRP). Time window service refers to the consumer as the foundation, made within the time constraints of a particular service and tasks. Delivery vehicles should consider carrying capacity and distribution distance and ensure the

vehicle number and minimum distance [19]. Scholars at home and abroad have conducted many studies on the VRP. Rajabi-Bahaabadi *et al.* constrained the time window in the model, punishing both early and late arrival, and finally solving the problem by combining the ant colony algorithm (ACO) with tabu search algorithm [20]. Xu H *et al.* proposed an ant colony optimization model combining the improved K-mean and cross operation to solve the dynamic VRP problem. This approach not only improves the search ability of the algorithm but also avoids the algorithm falling into the local optimum in advance [21]. Marianna Jacyna *et al.* studied the task assignment problem of vehicles in production enterprises from the perspective of resource allocation, constructed a multi-decision objective function, and completed the solution by using the improved genetic algorithm (GA) [22]. Considering factors such as soft time windows and heterogeneous vehicles, Amy H. I. Lee *et al.* adopted mixed-integer programming and GA to solve the multi-vehicle path planning problem [23].

In the era of big data, most e-commerce companies still fail to effectively use online review data to improve consumer satisfaction and fail to use consumers' delivery information to make reasonable path planning [24]. This situation of low sales and system chaos caused by the dislocation of individual e-commerce results in the urgent need for thought cognition and inadequate information utilization to be integrated and optimized from multiple directions. Consumers' wishes must be integrated into the development of e-commerce for rice and agricultural products and efforts should be made to improve consumer satisfaction to meet the long-term development of e-commerce. The starting point is the analysis of online reviews of rice e-commerce. On the basis of text mining analysis of 25,000 online reviews of rice e-commerce on JingDong (JD.com, JD), this paper concluded that the four factors of package integrity, delivery timeliness, door-to-door delivery, and service responsiveness were the logistics factors that most affected consumer satisfaction. A multi-objective model of packaging integrity, just-in-time delivery, and logistics cost under the soft time window is established. This model can satisfy the calculation of consumer satisfaction cost loss and e-commerce logistics control of distribution cost, and the practicality and effectiveness of the model are verified by an example. ACO and GA were used to solve the model, and the optimal number of vehicles and the optimal distribution path were obtained accurately. The research content of this paper is based on practical problems, which can provide a decision basis for the development of e-commerce logistics of rice agricultural products [25].

II. DATA COLLECTON AND PROCESSING
A. COMMENT ON DATA PROCESSING
To ensure the accuracy and representativeness of research data, online reviews of 25 e-commerce rice and agricultural products on JD were captured, and the total number of reviews of each e-commerce company was more than

1 million. The 1,000 latest reviews in chronological order were selected from each company as the research object. Next, 25,000 comments on JingDong Mall were captured, a total of 379 meaningless comments were removed, and then text analysis was performed.

1) The custom word list was supplemented. Due to the complexity of the main group of online comments and the different ways of language expression, some colloquial comment words, such as "tight" and "leak," appeared. In addition, some professional e-commerce words, such as "home delivery" and "next day arrival," cannot be accurately identified in the original lexis of ROST software, so specific words are added to supplement the customized lexis to ensure the authenticity and validity of research data.

2) The filter word list is supplemented. After the word segmentation operation of the custom word list, a simple word segmentation data result can be obtained preliminarily, but this data result does not have the actual research nature because it does not exclude some words with no practical meaning according to the actual demand. The result mainly includes mood particles, degree adverbs, and non-meaning spoken words such as "of," "oh," "um that," "should," and "really." Therefore, using the function of ROST software is necessary to gradually eliminate these words irrelevant to the actual research. In addition, some filtered words are preset in advance in the original software thesiology retrieval system, but they are related to the research of this paper. Such words include "speed," "activity," and "service." These two steps can ensure the accuracy of the word frequency statistics of the research object.

3) The merge word list is established. Given that consumers often describe the same feature in different expressions in the review process, this step is to ensure that a merged word list is constructed before word frequency analysis, and the synonymous expression word and synonym are replaced by a high-frequency word to ensure the integrity of the occurrence frequency of high-frequency words in the review.

B. SELECTION OF MAIN FEATURE WORDS
In this study, on the basis of the online comment data, through continuous merging and filtering of word segmentation, the words with the highest frequency in the comment process are finally obtained, which are the high-frequency words, as shown in Table 1.

The analysis results show that consumers have high requirements for product packaging and the frequency of related words in the high-frequency words accounts for 17.56%, indicating that consumers have expectations for the integrity of rice packaging. The delivery speed of rice agricultural products is also a high requirement. After shopping, consumers will very much expect the goods to arrive quickly and consciously compare the actual speed with the expected speed. If the former is far below the latter, consumer satisfaction will be seriously affected, showing that consumers pay considerable attention to timeliness in the process of commodity distribution. Door-to-door and related

TABLE 1. Summary of high-frequency words.

Serial number	High frequency words	quantity	Frequency
1	Packaging	29180	17.56%
2	Speed	22989	13.84%
3	Taste	22037	13.26%
4	Origin	13986	8.42%
5	Odor	13311	8.01%
6	Door-to-door	13168	7.93%
7	Services	12507	7.53%
8	Appearance	12476	7.51%
9	Express delivery	4558	2.74%
10	Flavor	4524	2.72%
11	Price	4413	2.66%
12	Quality	3855	2.32%
13	Brand	3630	2.18%
14	Activities	2241	1.35%
15	Fresh	1733	1.04%
16	Safety	1540	0.93%

TABLE 2. Weight ratio of each factor.

Factor	Integrity	Timeliness	Door-to-door property	Responsiveness
Weight	0.253	0.268	0.227	0.252

and (4).

$$r_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})} \tag{1}$$

$$p_{ij} = \frac{r_{ij}}{\sum\limits_{i=1}^{n} r_{ij}} \tag{2}$$

$$e_j = -\frac{1}{\ln n} \sum\limits_{i=1}^{n} p_{ij} \ln p_{ij} \tag{3}$$

$$k_j = \frac{1 - e_j}{\sum\limits_{j=1}^{m} (1 - e_j)} \tag{4}$$

A positive correlation is found between logistics distribution cost and door-to-door delivery index, that is, increasing door-to-door delivery service will naturally increase logistics distribution cost. Therefore, door-to-door weight is used to replace the weight value of distribution cost in the multi-objective function in this study. Responsiveness is mainly reflected in the initiative and spontaneity of businesses to provide convenient services for consumers. Given that this factor is difficult to quantify accurately, this study builds a model with packaging integrity, delivery timeliness, and delivery cost as the targets. After normalization, the weight value of the objective function determined is expressed as follows: the transportation cost (a_1) is 0.304, the integrity (a_2) is 0.338, and the timeliness (a_3) is 0.358.

words account for as much as 7.93% of the high-frequency words, which is also in line with the logistics enterprises using door-to-door delivery as a means to attract existing and potential customers. Consumers attach equal importance to responsiveness, which is mainly reflected in the initiative and spontaneity of businesses to provide convenient services for consumers.

In the high-frequency words, factors such as taste, place of origin, smell, and appearance also account for a high proportion, but these are the quality characteristics of rice agricultural products, which are affected by soil quality and climate, not by some links of e-commerce. Consumers can choose different types of rice products according to their personal preferences. E-commerce logistics is service-oriented work that can make adjustments according to the analysis of consumer feedback information, provide corresponding services, or improve the shortcomings of sales links to improve consumer satisfaction. To sum up, completeness, timeliness, door-to-door, and responsiveness are the four logistics factors to which consumers pay the most attention in the process of purchasing rice agricultural products.

C. ENTROPY WEIGHT METHOD TO DETERMINE THE WEIGHT OF FEATURE WORDS

The weight obtained by the entropy weight method is an objective weight, which mainly uses the entropy value of information to represent the uncertainty of information to calculate the level of the influence of evaluation indexes on decision information [26], [27]. In this paper, entropy weight processing is performed on the number of comments about high-frequency words extracted from 25 e-commerce companies, and the weight values of four factors as shown in Table 2 are obtained by calculating formulas (1), (2), (3),

III. MODEL CONSTRUCTION
A. MODEL OBJECTIVES

Through the analysis of 25,000 online comments on JD.com, the four logistics factors that consumers value most are the integrity of packaging, timeliness of delivery, door-to-door delivery, and responsiveness of service. However, the distribution cost has always been an important factor affecting the survival and development of enterprises, so the problem of e-commerce logistics distribution needs to be solved after the integration of resources to be able to have a distribution scheme that can not only improve consumer satisfaction but also reduce the distribution cost.

This paper constructs a model to solve the problem can be described as starting from the fixed logistics distribution center of distribution, how to arrange delivery routes, and distribution vehicle number. The objective is to make the distribution task guarantee economic benefit and social benefit maximization and implement the following three goals: (1) being on time, improving the quality of on-site service; (2) maintaining packaging integrity, reducing the probability

of packaging damage; and (3) reducing distribution cost and improving the competitiveness of logistics enterprises.

B. MODEL HYPOTHESIS AND SYMBOL DESCRIPTION

Given that JD's self-run stores mainly provide door-to-door delivery service, this paper builds a model on the basis that rice and agricultural products are delivered to communities by couriers. The actual study found that in the process of logistics distribution, the damage rate of commodity packaging would increase with each additional loading and unloading process. When the rice that was not delivered within the time range would be returned to the logistics distribution center, consumer satisfaction would decrease. In addition, the courier communicates with consumers about the delivery time before delivery, in line with the soft time window model. Therefore, this paper uses the penalty function to express consumers' satisfaction with the punctual arrival of rice agricultural products and the completeness of packaging [28]. Based on the facts of daily life behaviors and combined with the research focus of this paper, the following hypotheses are made:

(1) The distribution vehicle starts from the logistics distribution center (fixed), assuming the maximum mileage of the vehicle or parked in the logistics distribution center after finishing the service.

(2) When the distribution scope is determined, the logistics distribution center only considers the distribution business of rice agricultural products in the service area.

(3) The distribution center checks all orders accurately before each delivery, and different types of rice and agricultural products can be mixed.

(4) Each transport vehicle can serve multiple consumer sets (taking the community as the unit), but each consumer set cannot be delivered jointly by multiple vehicles.

(5) If rice agricultural products are not delivered to consumers on time within the specified time, then the agricultural products cannot complete the distribution and return to the logistics distribution center.

(6) The carrying weight of each transport vehicle is known, no overload will occur in the transportation process;

(7) The transportation process is unaffected by unexpected conditions such as the weather, vehicle failure, and road maintenance;

(8) The delivery vehicle has been driving at a constant speed and the transportation cost of the delivery vehicle per kilometer is the same;

(9) The logistics distribution vehicle stays at each consumer collection for the same time, that is, the unloading time is the same [29].

Parameter symbols are defined as follows:

n : Number of consumer groups;

i, j : Collection of consumer groups, ($i = 1, 2, 3, \cdots , nj = 1, 2, 3, \cdots , n$);

m : Number of delivery vehicles;

k : Distribution vehicle number collection, ($k = 1, 2, 3, \cdots m$);

n_k : Number of consumers served by the k delivery vehicle;

R_k : k delivery car serves the collection of consumers;

d_{ij} : Distance between consumer group i and consumer group j;

$L_{\max}$: Maximum driving distance of the delivery vehicle;

Q : Maximum load of the distribution vehicle;

C_i : Demand of consumer group i;

Z : Objective function;

V : Cost per kilometer;

L_{Rk} : Total mileage traveled by vehicle k on the path;

TRK : Total waiting time of vehicle k in the path;

S_i : Consumer i the moment the delivery task begins;

$p(i)$: Penalty cost obtained by the transport vehicle serving consumer i at time S_i;

F_i : Minimum value of penalty cost loss due to the transporter arriving at the consumer i in advance;

G_i : Minimum value of penalty cost loss due to the delay of transport vehicle arriving at consumer i;

α_i : Positive coefficient of penalty cost of transportation vehicle arriving in advance;

β_i : Positive coefficient of the penalty cost of delayed arrival of transport vehicles;

ET_i : Starting point of the time window reserved by the consumer;

LT_i : End point of the time window for consumer reservation;

E_i : Starting point of the time window acceptable to consumers;

L_i : End point of the time window acceptable to consumers;

σ_i : Maximum time difference acceptable to consumers;

M : Maximum penalty cost;

x_{ik} : Penalty cost coefficient of waiting time;

$$
y_{ik} = \begin{cases} 1 & \text{Agricultural products of collection} \\ & i \text{ are delivered by Car } k \\ 0 & No; \end{cases}
$$

$$
x_{ijk} = \begin{cases} 1 & \text{Transporter } k \text{ goes from set } i \text{ to} \\ & \text{set } j \\ 0 & No; \end{cases}
$$

C. MATHEMATICAL MODEL

1) LOWEST TOTAL TRANSPORTATION COST

In this paper, the transportation cost of each kilometer of distribution vehicles is assumed the same, so the lowest transportation cost can be translated into the problem of the shortest total distribution distance. L_{RK} represents the total mileage traveled by vehicle k on the route, namely:

$$
L_{Rk} = \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ijk} \tag{5}
$$

Therefore, the lowest total distribution cost is:

$$
\min \sum_{k=1}^{m} L_{Rk} = V \cdot \sum_{k=1}^{m} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ijk} \tag{6}
$$

2) HIGHEST PACKAGE INTEGRITY

If the rice and agricultural products loaded on the same day cannot be delivered within the time agreed to by the consumer, the rice and agricultural products will return to the logistics distribution center with the distribution vehicle, increasing the penalty cost. $p(i)$ represents the penalty cost obtained by the transport vehicle when serving the consumer at the moment S_i:

$$p(i) = \begin{cases} M & s_i < E_i \\ F_i + \alpha_i(ET_i - s_i) & E_i \leq s_i < ET_i \\ 0 & ET \leq s_i \leq LT_i \\ G_i + \beta_i(s_i - LT_i) & LT_i < s_i \leq L_i \\ M & s_i > L_i \end{cases} \quad (7)$$

Therefore, the highest package integrity means the minimum total penalty cost:

$$\min \sum_{i=0}^{n} p(i) \quad (8)$$

3) ARRIVE ON TIME

T_{Rk} represents the total waiting time of vehicle k in the path, namely, the sum of the waiting time for all consumers to arrive in advance served by the delivery vehicle on the path, namely:

$$T_{Rk} = \sum_{i=0}^{n} \max(ET_i - s_i, 0) \times x_{ik} \quad (9)$$

Therefore, the shortest waiting time is:

$$\min \sum_{k=1}^{m} T_{Rk} = \sum_{k=1}^{m} \sum_{i=0}^{n} \max(ET_i - s_i, 0) \times x_{ik} \quad (10)$$

The multi-objective problem can be converted into a single-objective problem through sorting, and its specific function is expressed as follows:

$$\min Z = \min \begin{bmatrix} a_1 V \\ \sum_{i=0}^{n} d_{ij} x_{ijk} \\ \sum_{k=1}^{m} \sum_{i=0}^{n} + a_2 \sum_{i=0}^{n} p(i) \\ + a_3 \sum_{k=1}^{m} \sum_{i=0}^{n} (ET_i - s_i, 0) \\ \times x_{ik} \end{bmatrix} \quad (11)$$

The objective function has the following constraints:

(1) $\sum_{k=1}^{m} y_{0k} = k$: The starting point of each distribution car is the logistics distribution center;

(2) $\sum_{i=1}^{n} x_{i0k} = 1$: After the delivery vehicle service consumers gather, they directly return to the logistics distribution center;

(3) $\sum_{k=1}^{m} n_k = n$: All consumers in the service area can receive the delivery service;

(4) $R_{K_i} \cap R_{K_j} = \phi, \forall k_i \neq k_j$: Means that multiple delivery vehicles are not allowed to serve the same collection of consumers;

(5) $\sum_{j=1}^{n} x_{ijk} = y_{ik}$: In a delivery activity, the same car is only allowed to arrive at the same consumer gathering once, and it is not allowed to turn back after missing the service;

(6) $\sum_{i}^{n} r_i y_{ik} \leq Q$: Vehicle k is not allowed to be overloaded when undertaking this distribution activity;

(7) $\sum_{i=1}^{n} \sum_{j=1}^{n} x_{ijk} d_{ij} \leq L_{\max}$: The total mileage of the vehicle in the process of undertaking the distribution activities is not allowed to be greater than the approved mileage of the vehicle;

(8) $ET_i \leq s_i \leq LT_i$ or $0 < ET_i - s_i \leq \sigma_i$ or $0 < s_i - LT_i \leq \sigma_i$: constraints of soft time window range;

(9) $\sum_{i=0}^{n} (x_{ijk} - x_{jik}) = 0$: Arriving vehicles serving a consumer collection are the same as departing vehicles;

(10) $0 \leq n_k \leq n$: indicates that the number of consumer sets on the path is less than the total number of consumer sets in the service area;

(11) $x_{ijk} = 0 \text{ or } 1$; $y_{ik} = 0 \text{ or } 1$: The variable of the function is an integer constraint.

IV. DESIGN OF SOLVING ALGORITHM
A. ALGORITHM SELECTION

At present, three types of algorithms are used for solving this type of problem: precise, heuristic, and intelligent. (1) The precise algorithm is a method to obtain the optimal solution by using precise mathematical operations for a specific mathematical model. This method can obtain the exact solution of the problem, but the operation is large. When the constraints increase, the operation becomes more difficult and needs considerable time, so this method is generally used to solve small-scale problems. (2) The heuristic algorithm is a type of algorithm based on intuitionistic or empirical construction. This method has simple calculation steps and fast operation speed, but its global search ability is insufficient, and it cannot guarantee the whole solution space of the search problem. The result is generally a "satisfactory solution" or "near-optimal solution," which is suitable for solving small and medium-sized problems. (3) The intelligent algorithm refers to an algorithm in which scholars are inspired by natural laws and solve problems by imitating them. It has strong global search ability and can usually obtain satisfactory solutions with high accuracy within a limited time. Therefore, in solving the problem of vehicles with soft time windows, intelligent algorithms are consistently preferred. In the intelligent algorithm, ACO and GA can achieve better results such problems, so these two algorithms are commonly used to optimize vehicle distribution routes. In this paper, ACO and GA are used to solve the constructed model and practical problems.

ACO is simulated in the world of natural biological ant clustering routing behavior in foraging activity, a type of heuristic algorithm. ACO has a positive feedback mechanism and the advantages of parallel computing, strong robustness, giving ACO stronger applicability and performance to deal with path planning with time windows compared with other algorithms. Therefore, many scholars have conducted in-depth studies on ACOto solve the soft time window VRP [30]–[32].

GA is a parallel and efficient search method that adaptively optimizes the whole world by simulating the genetic and evolutionary process of organisms in the natural environment. Given that the GA has strong global search ability and the search process is very fast, it achieves good results in solving relatively complex path planning problems [33], [34].

B. ACO

The steps of ACO to solve the soft time window vehicle path planning problem are as follows:

Step 1: Initialize parameters. Enter the distance data d_{ij} between consumers, customer demand r_i, and consumer time window data. Set the number of cycles N_c and initialize $N_c = 0$. Let the maximum iteration number $N_{max} = 250$; The maximum load of the distribution vehicle Q=1500; The maximum driving distance of the distribution vehicle $L_{max} = 200KM$ (the approved load of the electric distribution vehicle in the urban area is 1.5 tons, and the factory standard driving range is 200km); Information heuristic factor $\alpha = 2.0$; Expectation heuristic factor B $\beta = 3.0$; Pheromone persistence $\rho = 0.5$.

Step 2: Randomly place M ants on nodes of the consumer collection.

Step 3: Construct the preliminary solution with probability. Individual ants choose to visit the consumer node according to the state transition probability formula. However, whether the increase in the transport volume of the next node will lead to overloading of vehicles or make the vehicle mileage exceed the specified mileage must be considered. If both of them exceed, the ants will return to the starting point and then serve other consumers from the starting point. When all consumers in the region have accepted the service, a loop is completed and an initial solution is built. Then, each ant will independently select the next node according to the amount of pheromones left on the road and the heuristic information (the distance between nodes). The probability $p_{ij}^k(t)$ of ants traveling from node i to node j is:

$$p_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha \cdot [\eta_{ij}(t)]^\beta}{\sum\limits_{s \in allowed_k} [\tau_{is}(t)]^\alpha \cdot [\eta_{is}]^\beta}, & j \in allowed_k \\ 0, & \text{Others} \end{cases} \quad (12)$$

$$\eta_{ij} = 1/d_{ij} \quad (13)$$

In the formula, $allowed_k = \{0, 1, 2, \cdots, n-1\} - tabu_k$ represents the set of consumers that ant k is allowed to select

in the next step, and $tabu_k$ represents the tabu table, which records all nodes that ant k passes currently.

When the kth ant prepared to go from point i to point j according to the established rules, it first judged whether the total amount of rice and agricultural products transported at point j exceeded the approved load weight of the vehicle. If so, $allowed(k, j) = 0$, and point j was recorded, and then point j was recorded in table $allowed_k$. If not, the next judgment will be made, that is, whether the total mileage of the vehicle at point j exceeds the approved mileage of the vehicle. If so, $allowed(k, j) = 0$, and j point will be recorded in table $allowed_k$; The last step is to judge whether the time window constraint is satisfied. If not, a=0 and point j is recorded in table A. If the time window constraint is also satisfied, point j is recorded in tabu table, and the next node is found from point j according to these rules.

Step 4: Update local pheromones. When all ants complete a cycle, the pheromone on the path needs to be updated. The specific formula is shown in (14) and (15).

$$\tau_{ij}(t+n) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij} \quad (14)$$

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{Q}{L_k}, & \text{When ant } k \text{ passes through} \\ & \text{path } ij \text{ in this cycle} \\ 0, & \text{Others} \end{cases} \quad (15)$$

where: $(1 - \rho)$ represents the persistence coefficient of pheromone and $\Delta\tau_{ij}$ represents the increment of pheromone on path ij in this iteration, expressed as:

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^k \quad (16)$$

$\Delta\tau_{ij}^k$ represents the amount of pheromone left on path ij by the kth ant in this iteration. If no ant passes through path ij, the value is 0. L_k is the length of all the paths taken by the kth ant in this cycle.

Step 5: If all ants complete a cycle, proceed to the next step, otherwise return to step 3.

Step 6: Update the global pheromone. When all ants complete a cycle, wait for multiple solutions, but only one shortest path is the optimal solution in this iteration process, so continue to update the pheromone on this path according to formula (17) and (18):

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (17)$$

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{Q}{L_{gb}}, & \text{If } ij \text{ is in the optimal solution} \\ & \text{of this iteration} \\ 0, & \text{Others} \end{cases} \quad (18)$$

where, L_{gb} is the optimal path of this iteration. The update of global pheromone belongs to the additional pheromone added to the shortest path of this iteration, which can play the role of enhancing pheromone.

Step 7: Repeat the above steps until the iteration reaches the maximum iteration value, and output the optimal solution [31], [35].

C. GENETIC ALGORITHM SOLUTION

GA is a process of generating a new generation of population and gradually evolving to close to the optimal solution through a series of operations such as selection, crossover, and variation of the current population by using the group search technology [36].

1) CHROMOSOME CODING

To improve the calculation accuracy of the algorithm, this paper adopts natural number coding, which can also effectively find the best permutation and combination, and intuitively express the driving path of the distribution vehicle. The set of 21 consumers are used, as are the numbers 1, 2, 3…The number 1 represents a distribution center, and each node represents a gene. Limited by factors such as the number of vehicles to be delivered, vehicle approved load, driving distance, and time window, the number 1 needs to be inserted into the gene sequence. For example, a group of sequences is randomly selected as (5, 8, 3, 7), and the number 1 is inserted into (1, 5, 8, 3, 7, 1) according to the limiting factors. Thus, the first vehicle starts from the distribution center; passes through nodes 5, 8, 3, 7; and finally returns to the logistics distribution center.

2) PARAMETER INITIALIZATION

Set the initial population number $N_p = 45$; Crossover probability $P_c = 0.5$; Mutation probability $P_m = 0.01$; Termination evolution algebra $G = 500$; The evolutionary algebra counter $g = 0$.

3) FITNESS CALCULATION

In the implementation of the algorithm, the priority distribution relationship is determined by the limitation of the time window and the distance between each consumer node and the distribution center. Under the condition of satisfying the constraint conditions, prioritizing delivery is reasonable if the delivery distance is short and the delivery service time meets the time window required by the customer. On this basis, if the limiting factors are violated, the penalty function in the objective function is used to reduce the fitness value of the function to be eliminated [32].

4) SELECT OPERATIONS

In this paper, the method of roulette is adopted to select the best adapted to the environment, which is based on a certain proportion of selection, using the principle that the greater the proportion of individual fitness, the easier the offspring will be retained. The probability of an individual being selected is expressed as:

$$p_i = \frac{f_i}{\sum_{i=1}^{N_p} f_i} \quad (19)$$

where, f_i represents the fitness of an individual and N_p is the size of the population. The greater the fitness of individuals,
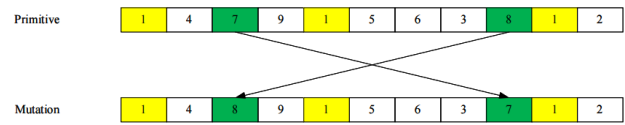

FIGURE 1. Variation operation process diagram.

the greater the chance of being selected. To select cross individuals, multiple rounds of selection will be carried out, and a uniform random number within [0, 1] will be generated in each round, and the random number will be used as the selection factor to determine the final selected individuals.

5) CROSS OPERATION

The selected individuals in the population are randomly combined, but for each pair of individuals, some chromosomes are exchanged with each other at a specified crossover probability (0.5 in this paper). The specific steps are as follows: first, take a pair of individuals from the randomly paired set, then randomly select one or more integer multiples of $[1, L-1]$ from the individuals to be mated as the crossover position according to the bit string length L, and finally carry out the crossover operation according to the crossover probability to exchange part of their genes to form a new individual.

6) VARIATION OPERATION

When no new individuals can be generated through the crossover operation, new individuals need to be generated again through the mutation operation to meet the global optimization characteristics of the increased algorithm. In this paper, the mutation operation with the corresponding gene value being reversed is adopted. The mutation probability set in this paper is 0.01. When this probability is reached, two gene loci are randomly selected from the optimal individual after selection and crossover operation to achieve the mutation operation [33], as shown in Figure 1.

7) TERMINATE THE OPERATION

In the operation process, if $g < G$, the operation will continue from step (3) until the individual with the maximum fitness and the optimal solution are output after the operation is terminated algebra [37].

V. CASE ANALYSIS
A. BASIC DATA

In this paper, the logistics distribution center and 21 consumer collection points are located in Xuanwu District, Nanjing city. Baidu map is used to determine the specific location of the residential area. The central gate overpass is selected as the origin of the coordinate system to build a rectangular coordinate system, and the static environment in the region is shown in a two-dimensional plane (the proportion is 1:50 meters).

Considering the influence of buildings and the natural environment in real life, the distance between each consumer set is not Euclidean, so this paper uses Baidu Maps to simulate

TABLE 3. Consumer collection information.

Numbering	Name	Position		Goods received （kg）	Service time window	
		X (cm)	Y (cm)		ET_i	LT_i
1	Logistics distribution center	9.2	2.8	300	9:00	19:00
2	Huangjia Garden	10	3	240	12:00	15:00
3	Taoyuan New Village	10	3.6	145	13:00	16:00
4	Zhong Lanli	10.8	3.2	380	15:00	18:00
5	Zhong Shan Yi Fu	10.2	4.6	150	13:00	17:00
6	Huangpu Garden	10.4	5.4	80	12:00	15:00
7	Huangpu Road No.4 Community	10	5.2	120	13:00	16:00
8	Dongda Yingbi Community	9.2	3.6	360	14:00	17:00
9	Sha Tong Garden	8.6	2	175	13:00	16:00
10	Heung Ju Mei Yuan	8.2	1.2	420	13:00	15:00
11	Kairun Jincheng	9.4	0.2	230	12:00	15:00
12	Yangtze River Garden	9.4	0.6	500	14:00	17:00
13	Beimenqiao Road High-rise Residential Quarter	9	0.8	90	14:00	18:00
14	Bluestone Garden	10.4	0.6	140	15:00	18:00
15	Weixiang community	8.4	1	40	13:00	16:00
16	Yi Xiang Community	8.4	1.6	160	15:00	18:00
17	Orchid Garden	7.8	3.2	40	13:00	16:00
18	Yanwu New Village	8	3.4	220	15:00	18:00
19	Taiping Garden	7.2	5.2	300	13:00	17:00
20	Yuexin Garden	7.6	5.4	430	13:00	16:00
21	Qingxi Garden	10.6	7	400	14:00	17:00
22	Jinling Imperial Garden	6.6	5	300	12:00	15:00

TABLE 4. Results of ACO.

Number of allowed delivery vehicles/ vehicles	Actual number of delivery vehicles/ vehicles	Objective function value	Total distance traveled/ km	Simulated total delivery time/min ute	Delivery completi on rate/%
3	3	1942	40.3	930.9	85.71%
4	4	1461	39.5	1018.5	95.24%
5	5	1491	46.8	1040.4	95.24%
6	4	2156	40.9	977.7	90.48%

FIGURE 2. Output diagram of the optimal solution of ACO.

driving between each consumer set and determines the actual distance between each node according to the best route recommended by the map. The collection received quantity and time window data of consumers on a certain day are shown in Table 3.

B. COMPARATIVE ANALYSIS OF RESULTS

The model was solved according to the data such as the actual distance of the consumer set, distribution quantity, and time window of consumer acceptance. The optimal distribution scheme was selected by changing the difference between the value of the objective function and the number of delivery vehicles. The results of the two algorithms are as follows:

The actual path is represented by nodes as follows, and the optimal solution output by MATLAB is shown in Figure 2:

Path 1-1-2-3-4-5-7-8-10-16-1;

Path 2:1-6-13-15-1;
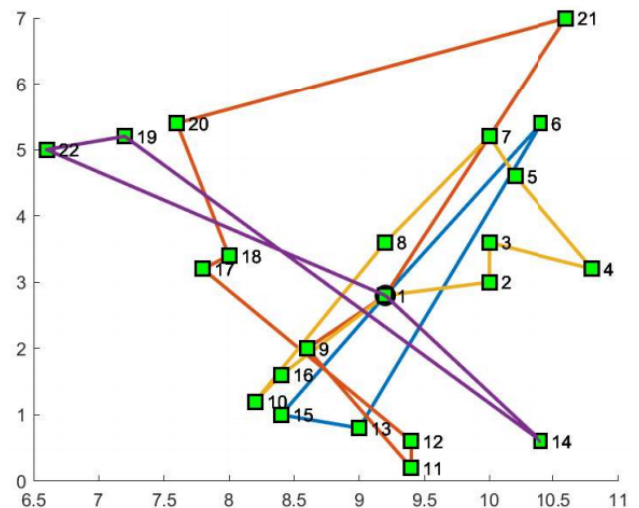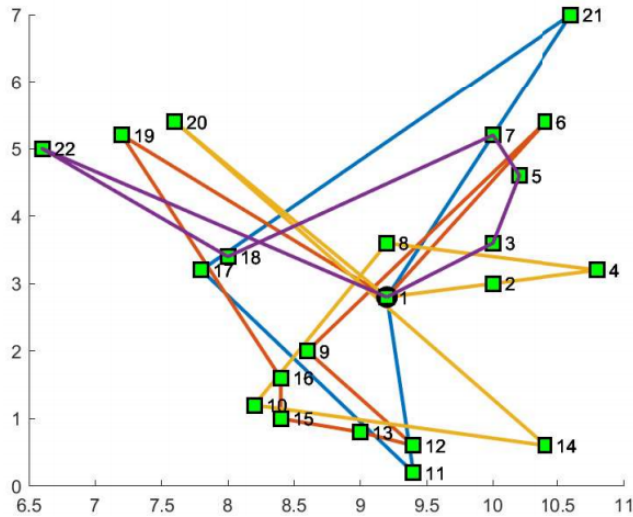
Path 3:1-9-11-12-17-18-20-21-1;

Path 4:1-14-19-22-1.

The model includes three objectives: the best package integrity, timely delivery, and lowest freight. A smaller value of the output objective function results in the optimal result being proved, that is, high consumer satisfaction and low delivery cost are met at the same time. A comparison of several schemes obtained by ACO shows that when the logistics distribution center carries out distribution with four vehicles according to the route shown in Figure 2, the best effect can be achieved, and 95.24% of consumers can complete the distribution task.

Similarly, GA is used to solve this model, and the result is that the solution of four logistics distribution vehicles to

TABLE 5. Operation results of GA.

Number of allowed delivery vehicles/vehicles	Actual number of delivery vehicles/vehicles	Objective function value	Total distance traveled/km	Simulated total delivery time/minute	Delivery completion rate/%
3	3	1810	37.7	968.1	90.48%
4	4	1555	47	996	90.48%
5	4	1699	37.3	966.9	90.48%
6	4	1579	42.6	982.8	90.48%

FIGURE 3. Output diagram of optimal solution of GA.

FIGURE 4. Optimal path convergence of ACO.

FIGURE 5. Optimal path convergence of GA.

complete the distribution can ensure the minimum value of the objective function, and the result is optimal. The results are shown in Table 5 and Figure 3. ACO and GA solve the vehicle path planning problem with a soft time window.

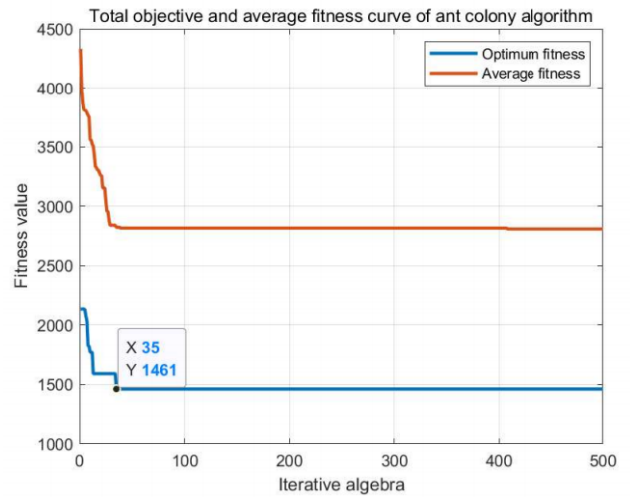The actual path is represented by nodes as follows:

Path 1:1-2-4-8-10-14-20-1;

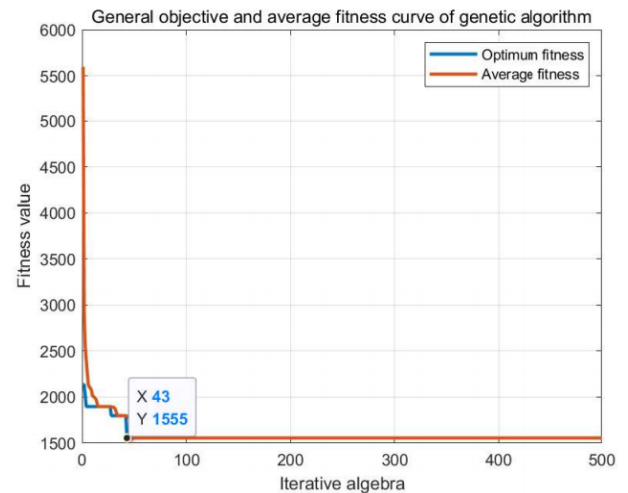Path 2:1-3-5-7-18-22-1;

Path 3:1-6-9-12-13-15-16-19-1;

Path 4:1-11-17-21-1.

Although both algorithms can obtain the same number of delivery vehicles and almost the same route arrangement, major differences remain between them. A comparison of Tables 4 and 5 show that in the optimal scheme, the fitness value of GA is 6.05% higher, the distance traveled is 15.96% more, and the completion rate is 4.76% lower than that of ACO. The ACO is superior in solving this example.

A comparison of Figures 4 and 5 shows that with the increase of the number of iterations, the average fitness gradually converges, and the total objective value of the function tends to be minimized. The curve of the ACO reaches stability after 35 iterations, indicating that the ACO can find the optimal path at this time. The GA finds the optimal path after 43 iterations. The comparison shows that the convergence speed of ACO is faster than that of GA, and the total target value of ACO is better when solving the model.

To verify the effect of the two algorithms in solving the model, the effect of the algorithms when the number of nodes is 50, 100, 250, and 500 are verified respectively. These node coordinates, cargo quantity, and time constraints are randomly generated by MATLAB, and the results are shown in Table 6.

The results show no significant difference between the fitness values of the two algorithms when 50 nodes are used. Although the ACO has a slightly better effect, it does not show obvious advantages like the example, and the calculation time of the GA is 12.4% lower than that of the ACO. When the number of nodes is 100, the fitness accuracy of GA is 36.2% higher than that of ACO, and the operation time is 8.96% lower than that of ACO. When the number of nodes is 250, the fitness accuracy of GA is increased by 43.5% and the operation time is reduced by 8.49%. When the number of nodes is 500, the two indexes of GA are increased by 40.6% and decreased by 13.7%, respectively.

TABLE 6. Comparison and analysis table of multiple data.

Node	Ant colony algorithm							Genetic algorithm						
	M	G	Z	m	S	L	P	N_P	G	Z	m	S	L	P
50	55	500	2762	8	16.67	314.4	95%	55	500	2849	8	14.61	353.78	95%
100	100	1000	7600	15	120.27	695.8	79%	100	1000	4847	16	109.49	625.4	95%
250	200	1500	23330	33	655.80	1690	74%	200	1500	13170	32	600.13	1968	85%
500	200	1500	51460	71	1575.4	3395	76%	200	1500	30590	71	1359.5	3357	86%

Two conclusions can be drawn by comparing the results of the two algorithms. First, the number of nodes affects the fitness value of the algorithm. When the number of nodes is less than 50, the ACO is better, but when the number of nodes is more than 100, the fitness value of the GA is better. Second, the operation time of the two algorithms increases with the increase of the number of nodes, but the consumption time of GA is always lower than that of ACO, and the average consumption time is reduced by 12.28%. In conclusion, when solving this type of model, ACO is suitable for the operation of a small amount of data and can ensure the accuracy of the results, while GA is more suitable for the operation of a large amount of data.

VI. CONLUSION

On the basis of the perspective of consumer satisfaction, this paper captures and analyzes online reviews of JD.com's rice and agricultural product e-commerce and finds that the four logistics factors that consumers value most are package integrity, delivery timeliness, door-to-door delivery, and service responsiveness. To improve consumer satisfaction and reduce delivery cost, a multi-objective model under a soft time window was constructed, and the effectiveness and practicability of the model was proved by comparing ACO and GA. ACO has faster convergence when solving vehicle path planning problem models with a small amount of data with a soft time window, and its accuracy is higher than that of GA. However, the comprehensive performance of GA is better than that of ACO when solving models with a large amount of data. The equalization efficiency of GA is 12.28% higher than that of ACO.

From the perspective of consumers, this paper analyzes tens of thousands of real online review data through text mining. Compared with traditional questionnaire surveys, text mining can more accurately express the real opinions of consumers, making research results more consistent with reality and more valuable for reference. In addition, the multi-objective optimization model can satisfy the calculation of cost loss of consumer satisfaction and the control of distribution cost of e-commerce logistics, providing a reference for relevant enterprises to arrange distribution schemes.

Although this paper studies the multi-objective planning of e-commerce logistics based on online review data of the JD e-commerce platform and obtains results for reference, with the development of rice agricultural products e-commerce, data of more large-scale e-commerce platforms can be analyzed and studied. In addition, other methods such as simulated annealing algorithm and tabu search algorithm can be used to solve the model to seek the optimal distribution scheme to better promote the development of e-commerce logistics of rice agricultural products. E-commerce platform sellers publicize the factors that consumers are concerned about, so as to stimulate consumers' purchase intention. Logistics enterprises improve product packaging, logistics distribution and other aspects to meet consumers' current needs.

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