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Research on Service Quality Improvement of Takeaway Platform Based on Artificial Intelligence

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ABSTRACT

Service quality is the key for takeaway platforms to maintain their advantages in the fierce market competition. In this study, we construct a mathematical model to solve the takeaway delivery problem by ant colony algorithm, so as to realize the takeaway delivery path planning based on ant colony algorithm. The grey neural network model is used to predict the order demand in the takeaway platform, and the fruit fly algorithm is used to fine-tune and optimize the parameters in the grey neural network model to avoid the model from falling into the local optimum and to improve the accuracy of the model in predicting the takeaway demand. Through simulation experiments, it is found that the planning algorithm in this paper can successfully realize the reasonable planning of takeaway delivery paths when the initial positions of merchants, users and delivery workers are known. The gray neural network optimized using the fruit fly algorithm is also able to accurately predict the takeout demand of platform users based on the order data provided by the takeout platform. Using the method of this paper for the improvement of the service quality of the takeaway platform can significantly improve the delivery efficiency of takeaway orders and develop personalized service strategies according to user demand, thus enhancing user satisfaction with the takeaway platform.

Keywords: ant colony algorithm, fruit fly algorithm, gray neural network, path planning, quality of service

1. Introduction

Along with the gradual integration of the Internet industry into social life, the rapid development of the Internet industry, the catering industry's marketing approach also ushered in a huge development opportunities and challenges. In addition to the traditional advantages of dine-in, the catering takeaway mode has also emerged under the wave of "Internet + Catering". In the increasingly competitive situation of the catering industry, takeaway has become an important means to promote the economic development of the catering market [1-2]. However, with the booming development of

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the takeaway industry, a large amount of capital pours into the takeaway market, which has an important impact on the development of the takeaway industry. At the same time, along with the rapid development of the takeaway industry, some takeaway platforms also have problems such as poor service quality, low delivery efficiency and poor hygiene, resulting in poor consumer satisfaction with the takeaway platform. Therefore, improving the service quality of takeaway platforms with the help of artificial intelligence is of great significance to improve the satisfaction of takeaway customers as well as the development of the whole takeaway industry [3-6]. Artificial intelligence is conducive to improving the convenience of ordering food, optimizing delivery efficiency and improving after-sales service in takeaway platforms, which overall improves the service quality and user experience of takeaway platforms. However, some potential problems need to be alerted at the same time. The application of AI in takeaway platforms may lead to homogenization of consumer choices, which may weaken market competitiveness, and more importantly, AI increases the risk of user data security and privacy leakage [7-9].

Literature [10] aims to validate the relationship between service quality and service satisfaction in O2O takeaway services, revealing that O2O couriers must improve the level of service requested by customers when there are problems with their orders, thus increasing customer satisfaction. Literature [11] describes how chatbots integrated with blockchain can effectively improve the efficiency, transparency and trust in the delivery process when integrated with IoT devices, and analyzes the application of blockchain, chatbot and IoT technologies in the food delivery industry, highlighting the advantages and potential impacts they offer. Literature [12] points out that with the development of big data, many takeaway platforms use algorithms in analyzing customer data, which effectively recommend goods with personalization for users, and also speed up delivery speed, which improves the shopping experience of users, but there are problems such as price discrimination and differential treatment, which seriously harms the rights and interests of users. Literature [13] examines a year-long participatory action project for which, in particular, parts of the takeaway platform JustEat were redesigned, emphasizing the opportunities and mechanisms for platform modifications that can enhance the connection with adversarial design and potentially improve the experience of platform users. Literature [14] presents a combined order selection and delivery path planning problem for a delivery provider with uncertain order lead times and customer satisfaction levels, proposes a hybrid evolutionary algorithm to evolve the solution of the master order selection problem, and shows that the algorithm has excellent performance. Literature [15] proposed a bi-periodic changing preference model for takeaway recommendation based on the shortcomings of takeaway recommendation systems, which outperforms other methods on real-world datasets, and applies it to takeaway platforms to achieve an increase in the total value of commodity transactions. Literature [16] outlines the current situation and key technologies of smart catering, and proposes the development direction of smart catering, which is centered on health, deliciousness, and culture, aiming to provide a reference for the advancement of the catering industry. Literature [17] describes the application of artificial intelligence in the food industry, which is conducive to reducing human errors, maximizing resource utilization, realizing substantial savings, and helping to improve the development of the entire food industry, such as restaurants, cafes, and online takeout chains. Literature [18] explored the impact of collaboration between restaurants and Mobile Food Delivery Applications (MFDAs) on product development efficiency and revealed that product development efficiency between restaurants and MFDAs is influenced by a number of factors, and that only a strong connection with MFDAs can ensure the availability of meals. Literature [19] developed an AI-based takeout platform where users can choose different suppliers for food purchases, which not only has features such as customizing the number and frequency of meals, but also helps housewives to start businesses at home and achieve economic independence.

This paper analyzes the takeaway service mode and service process of MT takeaway platform by taking it as the research object. According to the research results, the problems in the service process of the takeaway platform represented by MT are analyzed, which provides a direction guide for this paper to improve the service quality of the takeaway platform by using artificial intelligence technology. In view of the deficiencies in takeaway delivery efficiency, this paper constructs a mathematical model of the takeaway delivery problem and solves the model through the ant colony algorithm to realize the intelligent planning of the takeaway delivery path. Based on the obvious advantage that the gray neural network model shows in the development prediction problem of uncertain system characteristics and behavioral eigenvalues, this paper uses the gray neural network to construct the demand prediction model of the takeaway platform. At the same time, for the grey neural network in the training of the problem of falling into the local optimum, the use of fruit fly algorithm to fine-tune the optimization of the parameters in the network, to overcome the problem of local optimality at the same time to improve the model prediction accuracy of the demand for takeaway orders. According to the data provided by the takeaway platform, simulation experiments are carried out to analyze the feasibility and reasonableness of this paper's method in improving the service quality of the takeaway platform. It provides a reference for the scientific formulation of the service quality improvement strategy of takeaway platform.

2. Exploring service quality on takeaway platforms

The investigation of the service quality of takeaway platforms is the basis for the study of the service quality of takeaway platforms. This section takes the MT platform, which is a strong representative platform of Chinese takeaway platforms, as an example, and focuses on exploring the service content of the takeaway platforms and the existing problems in the service quality of the current takeaway platforms, in order to provide a research direction for the improvement of the service quality.

2.1. Introduction to the platform

On March 4, 2010, MT.com was officially founded, headquartered in Beijing, China. The purpose of MT.com is to find trustworthy merchants for consumers to enjoy high-quality and value-added services, and to provide merchants with the most profitable online promotional platforms to find the most suitable consumers for them.In November 2013, MT Takeaway APP was officially launched. At the beginning of the launch, MT Takeaway's service was focused on catering, and its target market was mainly the student group, creating a platform to meet consumers' needs for takeaway ordering.MT Takeaway's scope of service has become more and more extensive after continuous development, and in 2015, MT Takeaway added the flash shopping business, the same-city errand business and the medicine delivery service on the basis of providing catering takeaway delivery service, expanding the channels for consumers to purchase meals, desserts and beverages, fresh fruits and vegetables, flowers and greens, maternity and baby department store, cosmetics, clothing, pet supplies and other commodities. Apparel, pet supplies and other products, to the greatest extent possible to meet the personalized needs of customers. According to relevant data, as of 2020, the transaction value of MT Takeout business reached RMB 483.9 billion, a year-on-year increase of 24.38% from 2019, the annual active users reached 619.3 million trips, a year-on-year increase of 168.0 million from 2019, the number of cooperating merchants exceeded 6.25 million, the total number of delivery staff reached 3.984 million, and the business has covered China's 2,716 cities and counties, and the number of daily completed orders exceeded 39 million.

2.2. MT Takeaway Service Models and Processes

2.2.1. MT Takeaway Service Model. Currently, the service model of MT Takeaway includes three main types, namely MT Specialized Delivery, Merchant Delivery and Crowdsourcing Delivery.

1) MT Special Delivery. MT Dedicated Delivery is a self-constructed logistics and distribution mode of MT Takeout, which aims to provide consumers with better logistics services. MT Dedicated Delivery is based on the location of the delivery staff and uses the system to directly dispatch orders to the delivery staff, which can guarantee the order acceptance rate and delivery efficiency of the delivery staff. MT Dedicated Delivery's delivery staff are official employees of MT Takeout, with uniform uniform and strict management, fixed working hours every day, and are the main force to ensure the normal operation of MT Takeout's delivery service, with higher delivery costs. after joining MT Dedicated Delivery, MT Dedicated Delivery's delivery staff need to receive strict induction training and occasional professional training, and MT Dedicated Delivery's delivery staff have a higher level of professionalism and professionalism than those of crowdsourcing delivery and merchant delivery, so that the quality of service and efficiency of delivery can be ensured, but they also have the shortcomings of high delivery costs and restricted delivery areas, etc. However, there are also disadvantages such as high delivery costs and delivery area limitations.

2) Merchant Delivery. Merchant distribution refers to merchants responsible for their own distribution of goods, the use of this mode is mainly two types of merchants. One is a small-scale, short of funds merchants, such as neighborhoods, schools near the supermarket, restaurants and so on, this kind of merchants are only responsible for a small range of goods distribution, distribution range has certain limitations, if there is a peak period of distribution of too many orders, will not be able to guarantee the timeliness of the distribution and the quality of logistics services. Another category is the larger brand chain merchants, these merchants have strong capital, a large number of customer groups, can be equipped with sufficient, professional distribution staff, such as large-scale restaurant chains, distribution staff are merchants of their own formal staff, this distribution method is more costly, but can effectively ensure that the distribution of time and quality of logistics services.

3) Crowdsourcing Delivery. Crowdsourcing delivery is that MT Takeaway outsources takeaway orders to third-party delivery personnel to complete the delivery service in the form of free voluntary outsourcing. This delivery mode can effectively utilize the free time of social personnel, solve the problem of insufficient delivery capacity during peak periods, and to a certain extent, alleviate the delivery pressure of MT Takeaway. Most of the crowdsourcing delivery personnel are based on the individual's geographic location and free time schedule to grab an order for delivery, and the delivery personnel have a great deal of autonomy in terms of whether or not to accept the order delivery task. Crowdsourcing delivery workers also have relatively low recruitment requirements compared to MT delivery workers. There is no mandatory requirement for working experience, and all they need to do is to register in the crowdsourcing delivery-related apps and go through a simple online training program before they can start their jobs. Compared with MT Dedicated Delivery, the delivery range of crowdsourcing delivery is relatively larger and the cost is lower, but the delivery speed and the overall service quality of delivery personnel are lower than MT Dedicated Delivery.

2.2.2. MT Takeaway Service Processes. MT Takeaway, as a platform providing takeaway delivery service for consumers, can reflect the whole process of logistics service provided by MT Takeaway from the user placing an order to the completion of the whole delivery process.MT Takeaway service flow is shown in Figure 1. It mainly includes:

1) User ordering. After choosing the basic information such as the ordered goods, delivery address and delivery time in the takeaway APP, the user confirms the order and the order is automatically transferred to the corresponding merchant.

2) Merchants accept or reject orders. After a merchant receives a user's takeaway order in the ERP system of MT Takeaway Open Platform, the merchant chooses to accept the order to prepare for shipment and arranges for the corresponding delivery party to carry out takeaway delivery. If the merchant rejects the order or fails to accept the order within 5 minutes, the order will be automatically

canceled.

3) Delivery. According to the delivery method chosen by the merchant, the takeaway goods will be delivered to the customer's designated delivery location after being picked up by the merchant's delivery person, MT delivery person or third-party delivery person. The status of non-merchant self-delivery orders is updated according to the operation of the delivery person in the APP on the rider's end, and the merchant self-delivery orders are notified by the merchant by updating the order's delivery status to the customer.

4) Confirmation of delivery. The merchant or rider confirms the delivery of goods to the customer and then updates the delivery status on the APP to inform the customer that the goods have been delivered.

5) After-sales and feedback. If the goods are inspected or used by the user, and if problems such as damage, decay and shortage of quantity are found, the user can apply for refund, return and other after-sale services. After the user confirms that the goods are correct and undamaged, the user will evaluate and give feedback on the service quality of the seller.

6) Order fulfillment. After solving the after-sale problems and the user completes the feedback, the service process ends here.

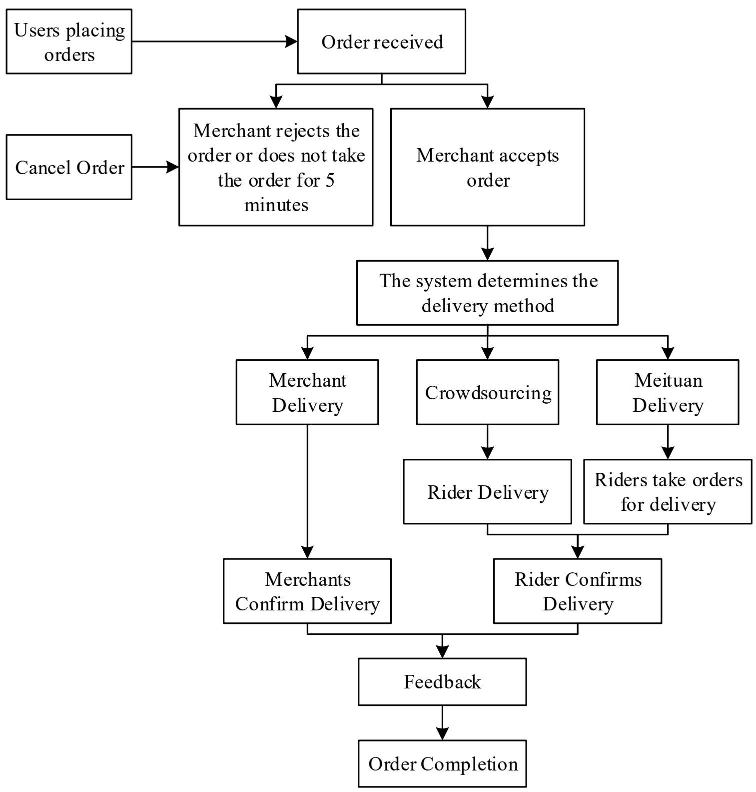


Fig. 1. Delivery service process

2.3. MT Takeaway Service Quality Issues

1) Takeaway delivery process is prone to accidents. In the delivery process, the takeaway delivery personnel will transport the goods from the merchant's address to the user's address, across the physical space is large, the experience time is long, and the goods are in the closed takeaway delivery box, the traffic condition, the weather condition, the operation error and other factors can lead to the occurrence of accidental conditions of the goods. Accidental conditions occurring in the delivery process include poor insulation of meals, incomplete preservation of commodities, loss of commodities, and errors in the verification of commodity information. Meanwhile, due to the one-way

nature of the delivery process, the delivery person is only responsible for completing the one-way delivery from the merchant to the user, and does not return to the merchant after the end of the service, so there is no opportunity to make secondary corrections to the commodity when the accidental condition occurs, and there is a big gap between the user's actual experience and expectation.

2) Incoherent delivery process. In the office scenario (non-enclosed environment), the takeaway delivery person and the user proactively use the indirect delivery method, where the takeaway delivery person places the goods at the designated place and then ends the service process and leaves the service scenario, lacking the link of checking the goods information with the user on a one-to-one basis, which is incoherent in information, and is solved by the existing platform through the way that the user can check the goods information on his/her own.

In the school scenario (semi-closed environment), the takeaway delivery person and the user adopt the common delivery method, the takeaway delivery person and the user go to the delivery place together to carry out the delivery behavior face-to-face, and the time consumed by both of them on the way is different, and the user often lags behind the takeaway delivery person, which is incoherent in time, and the user in the existing platform browses the real-time delivery map of the takeaway platform for several times, and prepares in advance or shortens the preparation time. Solution. The incoherence of information and time is disturbing to users, who passively perform compensatory behaviors, affecting their service experience.

3) Lack of spatial privacy. In home scenarios (closed environments), takeaway deliverers and users proactively use door-to-door delivery, in which the takeaway deliverer alerts the user of the arrival of the meal through the doorbell of the building and then directly arrives at the door of the user's house to deliver the meal. For ordering users, this delivery method poses security risks, as privacy is exposed on the one hand, and it is difficult to confirm the identity of the delivery person on the other hand, especially for female users. For security reasons, meal ordering users usually solve the problem by blocking space, delaying delivery, changing the deliverer, and changing the delivery location, which undoubtedly increases the interaction behavior and affects the user's service experience.

4) Delivery efficiency. Delivery service is mainly for small multi-volume orders, and there is a succession of orders in time, the takeaway delivery person completes the delivery service of the current order, and then immediately carries out the delivery service of the next order, which requires high delivery efficiency. In the whole service system, the delivery person is both a service provider and a service user in individual processes, and the existing service system does not consider the complex and difficult work of the delivery person from the perspective of a service user, and the service process, hardware equipment and software system cannot guarantee the delivery efficiency.

3. Strategies for improving service quality on takeaway platforms

With the development of the Internet and mobile payment technology, takeaway platforms are more and more frequently used in people's life scenes nowadays. As can be seen from the results of the previous survey and research on MT takeout platforms, the current takeout platforms still have certain service quality problems in the service process. To a certain extent, these problems affect the delivery platform's ability to provide high-quality services to users, reduce users' satisfaction with the delivery platform's services, and are not conducive to the creation of the platform's image and the enhancement of its market competitiveness. Therefore, this section will focus on exploring strategies to improve the service quality of takeaway platforms, using artificial intelligence technology to realize functions such as automatic planning of takeaway delivery paths, and improving the efficiency of takeaway delivery and other service contents, so as to improve the service quality of takeaway platforms.

3.1. Ant Colony Algorithm Based Path Planning for Takeaway Delivery

3.1.1. Description of the takeaway delivery problem. The takeaway delivery path planning problem studied in this paper can be described as the rational planning of a delivery driver's takeaway delivery path to improve the delivery efficiency and satisfy the constraints under the premise of satisfying the delivery driver's vehicle capacity constraints and delivery time window constraints [20]. For the problem studied in this paper can be simplified as the vehicle path problem with time window constraints and vehicle capacity constraints (CVRPTW). The mathematical model is described as follows:

Let K be the set of the total number of delivery agents in the takeout distribution center. N be the set of n customer points that need delivery service, $N=\{1,2,3,\cdots,n\}$, $V=\{0\}\cup N$:

$$\begin{aligned}&\min\sum_{k\in K}\sum_{i\in V_k}\sum_{j\in V_k\setminus|i|}C_{ij}x_{ij|k}\\&s.t.\sum_{j\in V_k\setminus|i|}x_{ij|k}=y_{i|k}\sum_{i\in V_k\setminus|j|}x_{ij|k}=y_{i|k}\end{aligned}\tag{1}$$

$$\forall i\in V,\forall j\in V,\forall k\in K \tag{2}$$

$$\sum_{j\in V_k}q_i y_{i|k}\le Q,\forall k\in K \tag{3}$$

$$\sum_{j\in N}x_{0j|k}=\sum_{i\in N}x_{i0|k}=1,\forall k\in K, \tag{4}$$

$$\sum_{k\in K}y_{ij|k}=1,\forall i\in N \tag{5}$$

$$\sum_{i,j\in V_k}x_{ij|k}\le|V_k|-1,\forall k\in K \tag{6}$$

$$T_{E,i}\le a_i\le T_{L,i},\forall i\in N \tag{7}$$

where: 0 is the distribution center. V_k is the set of vehicle visit customers. i,j denotes the customer number. $x_{ij|k}$ denotes whether the deliveryman k needs to deliver customer j after the delivery of takeout to customer i is finished. $y_{ij|k}$ denotes whether the deliveryman k has finished the delivery of takeout to customer i. Q indicates the deliveryman delivery takeout capacity constraint. q_i denotes the takeout demand of customer i. C_{ij} is the transportation cost for the deliveryman to drive from i to j point. $T_{E,i}$ is the earliest takeout delivery arrival time allowed by the customer i. $T_{L,i}$ is the latest takeout delivery arrival time allowed by the customer i. a_i is the deliveryman's arrival time at customer i. $x_{ij|k}$, $y_{ij|k}$ are decision variables when the deliveryman k makes a takeout delivery to the customer j after the takeout delivery to the customer i is complete, $x_{ij|k}=1$, otherwise $x_{ij|k}=0$. when the customer i makes a takeout delivery by the deliveryman k, $y_{ij|k}=1$, otherwise $y_{ij|k}=0$.

3.1.2. Distribution path generation. Deliveryman k departs from the place where customer i is located to the place where customer j is located at the moment the time is a_j. If a_j is greater than the right boundary of the time window of customer j, it will lead to the deliveryman delivering the takeout overtime, which is very likely to cause the customer to be dissatisfied with the evaluation such as poor evaluation, resulting in the damage of the interests of the deliveryman. Therefore, in the deliveryman delivery takeaway arrival time must be within the specified time window, the planned path is more reasonable for the deliveryman, need to be added in the state transfer process need to wait for the time of the influence factor.

The state transfer probability $P_{i,jk}(t)$ represents the probability that ant k moves from node i to node j at the t th iteration, and the movement rule is shown below:

$$j=\begin{cases}\max_{j\in N_{ilk}}\left\{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}\left[1/f_{widhh,,}\right]^{\gamma}\left[1/t_{w,j}\right]^{\delta}\right\} & r\le r_0\\ P_{ij|k}(t) & r>r_0\end{cases} \tag{8}$$

where: $P_{ij|k}(t)$ is the probability of selecting point j using the roulette method, which can be denoted as $\dfrac{\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}\left[1/f_{widh,j}\right]^{\gamma}\left[1/t_{w,j}\right]^{\delta}}{\sum_{j\in N_{i/k}}\left(\left[\tau_{ij}(t)\right]^{\alpha}\left[\eta_{ij}(t)\right]^{\beta}\left[1/f_{widhl,j}\right]^{\gamma}\left[1/t_{w,j}\right]^{\delta}\right)}$. N_{ilk} is the set of nodes that have not been visited by the ant colony and can be selected as the next node by the probability value. $\tau_{ij}(t)$ denotes the amount of pheromone on the edge formed by node i and node j at the t th iteration. α denotes the amount of influence of pheromone on ant colony search. $\eta_{ij}(t)$ denotes the magnitude of visibility of the formed edge to the ants, $\eta_{ij}(t)=1/d_{ij}$, d_{ij} are the distances from node i to node j. β is the effect of visibility on ant colony search. γ denotes the magnitude of the influence of the time window span factor leading to node selection by the ants. δ denotes the magnitude of the waiting time factor leading to the ants' influence on node selection. r is a random variable obeying uniform distribution on $[0,1]$. r_0 is a parameter controlling the transfer rule, and $0\le r_0\le 1$.

After visiting that path, the ant will leave a pheromone on that path, which acts as a guide for other ants. After each iteration, the ants will repeatedly pass the path, which will make the pheromone update, and the expression of the pheromone is:

$$\tau_{ij}(t+1)=(1-\rho)\tau_{ij}(t)+\sum_{k=1}^{n}\Delta\tau_{ijk}(t) \tag{9}$$

$$\Delta\tau_{ij,k}(t)=\begin{cases}Q/L_k & j\in V\\ 0 & Other\end{cases} \tag{10}$$

where: ρ is the pheromone volatilization factor of size $0<\rho<1$; $\Delta\tau_{ijk}(t)$ is denoted as the pheromone left behind by the k th ant passing through the path of the t th iteration, and the initial $\Delta\tau_{ijk}(0)$ is set to $1; L_k$ denote the total path length from the distribution center to the return visit of the k th ant to the distribution center. Q is set as a constant.

So that a group of ants from the distribution center, each ant in accordance with the rules of equation (8) to choose the next visit node j, when according to the rules can not find a reasonable next node j, the ants return to the distribution center, then the distribution path corresponding to the ants planning is complete, a group of ants all traversed nodes, that is, to generate the distribution path of the planned takeout.

3.2. Takeaway Demand Forecasting Model

3.2.1. Drosophila Algorithm. The fruit fly algorithm is mainly based on the fruit fly's sharp olfactory system's superb ability to perceive the flavor of things [21]. The stronger the flavor of the food, the stronger the ability of the fruit rope to perceive it, and the concentration of the flavor of the food for the fruit fly, the fruit fly search for food is a continuous process from the small taste to reach the taste of the place of the more intense. Where n fruit fly flies from the initial position of the fruit fly group in a random direction, and then all then fly to the position of the fruit fly with the highest concentration of food flavor to form a new position of the fruit fly group, and then fly out again, and so on and so on until the food source is found.

3.2.2. Gray Neural Networks.Gray models (GM) are differential equations based on raw data series. The most representative model in gray modeling is the GM for time series, which directly transforms time series data into differential equations. The system information is utilized to quantify the abstract model and thus predict the system output in the absence of knowledge of the system characteristics.The GM model firstly does a cumulative sum of the original data series so that the cumulative data shows a certain pattern, and then fits the curve with a typical curve.

Gray problem is the problem of predicting the development and change of the characteristic behavioral eigenvalues of the gray uncertain system characteristics, the original series of the eigenvalues of the uncertain system after a cumulative generation of the series, showing an exponential growth law, and thus can be a continuous function or differential equation for data fitting and prediction of the gray neural network [22] to the combination of the use of the gray model and the neural network, the full combination of the gray model model's simplicity, poor information processing ability and neural network's strong computation, error correction ability, in order to improve the accuracy of the prediction results.

3.2.3. Drosophila Optimized Gray Neural Network Prediction Model. Optimization of grey neural network prediction model according to the principle of Drosophila algorithm Drosophila optimization algorithm is used to iteratively and dynamically fine-tune the grey neural network model parameters a, b_1, b_2, b_3, b_4, b_5, so that the model detection ability is improved and the best grey neural network model parameters are obtained for prediction, as detailed below:

1) Parameter initialization. In the parameter setting of the Drosophila optimization algorithm, randomly initialize the Drosophila population position interval x_{axis}, $y_{axis} \in [-10,10]$, iterative Drosophila food-seeking random flight distance interval $R \in [-10,10]$, population gauge $sizepop = 20$, while the number of iterations $maxgen = 100$.

2) Initial evolution. Set the initial iteration number to 0, and set the individual fruit fly I food-seeking random flight direction $rand()$ and flight distance. Where $rand()$ denotes an arbitrary value generating function. In the Drosophila optimization gray neural network program, two variables $[X(i,:), Y(i,:)]$ are used to describe the flight distance of Drosophila individuals i. Set respectively:

$$\begin{cases} X_i = x + 10 * rand() - 10 \\ Y_i = y + 10 * rand() - 10 \end{cases} \tag{11}$$

3) Preliminary calculations and data preprocessing. Calculate the distance Dist from the origin for Drosophila individual i and the odour concentration judgement value S_i. which:

$$\begin{cases} Dist(i) = \sqrt{X_i^2 + Y_i^2} \\ S(i) = 1/\sqrt{Dist(i)} \end{cases} \tag{12}$$

In the Drosophila Optimal Grey Neural Network procedure, $D_{(i,1)}, D_{(i,2)}, D_{(i,3)}, D_{(i,4)}, D_{(i,5)}, D_{(i,6)}$ is used to denote Dist and $S_{(i,1)}, S_{(i,2)}, S_{(i,3)}, S_{(i,4)}, S_{(i,5)}, S_{(i,6)}$ is used to denote S_i. Input S_i into the Drosophila Optimization grey neural network prediction model for takeaway order quantity prediction. In the Drosophila Optimization Grey Neural Network procedure, parameter $a, b_1, b_2, b_3, b_4, b_5$ is represented by $S_{(i,1)}, S_{(i,2)}, S_{(i,3)}, S_{(i,4)}, S_{(i,5)}, S_{(i,6)}$. With the prediction results, the odour concentration value Smelli (or known as the fitness function) can be calculated. This odour concentration Smelli characterises the error between the predicted and actual values of the network output through the mean square error (RMSE).

4) Generation of population offspring. The population offspring are generated by steps 2) to 3) of the Drosophila algorithm and then fed into the grey neural network model to recalculate the odour concentration value, iteratively plus one, set to $gen = gen + 1$.

5) The loop ends. When the maximum number of datasets is reached, the stop condition is satisfied and the best parameters of the grey neural network model are obtained. If not, return to perform step 2).

4. Simulation experiments and analyses

4.1. Takeaway Delivery Path Planning Experiment

4.1.1. Data preparation. In order to solve the problem with a concrete example, a set of specific takeaway delivery orders generated in the region during the peak lunchtime period was obtained through a visit and investigation and the information provided by a delivery company in charge of the takeaway business in a certain region. The starting points of the takeaway orders and the corresponding locations of the delivery staffs responsible for delivering these orders were marked on the map through fieldwork and map software. According to the latitude and longitude values of these locations in the map to design a reasonable two-dimensional right-angle coordinate system, these latitude and longitude values are designed as coordinate points, in order to facilitate the calculation, the travelling distance is based on the distance between any two points, and the calculation method adopts the Euclidean distance calculation. And through the merchants and customers to visit the understanding, designed to meet the merchants want to keep the food fresh and taste good hope under the pick-up time window, as well as in line with the customer wants to eat at the best time to eat, do not want to wait too long under the idea of delivery time window. The specific order information values and the location information of the delivery person responsible for delivery in that area of the city are shown in Table 1 and Table 2. Based on the two location information tables, the straight line distance between any two path nodes and the distance travelled by the deliveryman to any node can be calculated by Euclidean distance calculation consensus. Through the investigation of the delivery person, it is known that the average speed of the delivery person in the process of delivery is $v = 150m / \min$, and then the time taken by the delivery person to pass through each node in the delivery path can be calculated according to the formula, taking the delivery time of a delivery person as an example, the result is shown in Figure 2, the number "0" in the figure represents the distribution center, "1-6" represents the business number, and "7-12" represents the user number.

Table 1. Order information

Merchant number	User number	Merchant position	User position	Pick up time window	Delivery time window
1	26	(2.61,7.48)	(2.03,8.19)	[0,10]	[0,35]
2	27	(1.92,7.41)	(2.11,6.67)	[0,10]	[0,31]
3	28	(2.66,7.13)	(1.95,8.06)	[0,10]	[0,36]
4	29	(1.94,7.39)	(0.53,6.72)	[0,10]	[0,43]
5	30	(2.23,7.44)	(2.34,7.47)	[0,10]	[0,33]
6	31	(1.98,7.39)	(2.69,7.43)	[0,10]	[0,36]
7	32	(2.61,7.43)	(3.98,8.31)	[0,10]	[0,32]
8	33	(3.43,6.87)	(1.09,6.74)	[0,10]	[0,38]
9	34	(1.98,6.82)	(2.28,7.39)	[0,10]	[0,34]
10	35	(2.55,6.98)	(0.41,7.23)	[0,10]	[0,35]
11	36	(2.93,7.44)	(3.74,8.59)	[0,10]	[0,31]

12	37	(2.74,7.99)	(3.44,8.47)	[0,10]	[0,43]
13	38	(2.67,7.32)	(2.36,7.38)	[0,10]	[0,31]
14	39	(2.61,7.09)	(1.29,5.96)	[0,10]	[0.43]
15	40	(1.98,6.82)	(1.54,5.87)	[0,10]	[0,47]
16	41	(1.93,6.87)	(2.36,8.34)	[0,10]	[0,49]
17	42	(2.85,7.23)	(4.48,8.31)	[0,10]	[0,43]
18	43	(1.95,6.84)	(1.53,5.87)	[0,10]	[0,36]
19	44	(2.71,7.13)	(2.36,8.34)	[0,10]	[0,34]
20	45	(1.94,7.39)	(1.77,6.98)	[0,10]	[0,37]
21	46	(1.92,7.36)	(1.89,7.41)	[0,10]	[0,31]
22	47	(2.67,7.05)	(1.93,7.09)	[0,10]	[0,39]
23	48	(3.14,7.48)	(2.83,7.34)	[0,10]	[0,27]
24	49	(2.77,7.19)	(1.92,6.74)	[0,10]	[0,29]
25	50	(1.95,7.32)	(3.61,9.14)	[0,10]	[0,44]

Table 2. Position information of delivery person

Delivery personnel number	Position	Delivery personnel number	Position
1	(1.17,5.54)	16	(2.13,6.89)
2	(3.32,6.68)	17	(3.35,5.74)
3	(0.87,7.51)	18	(1.89,6.03)
4	(2.59,7.48)	19	(2.44,5.98)
5	(2.53,5.91)	20	(1.22,6.54)
6	(2.17,8.54)	21	(1.67,7.19)
7	(1.62,5.34)	22	(2.69,7.28)
8	(3.89,6.13)	23	(3.14,7.58)
9	(2.93,8.39)	24	(2.49,8.23)
10	(4.22,7.37)	25	(2.16,5.89)
11	(3.69,8.33)	26	(1.67,7.98)
12	(3.91,7.04)	27	(2.11,8.43)
13	(3.74,5.58)	28	(2.14,7.36)
14	(3.92,5.74)	29	(3.42,7.16)
15	(2.47,6.69)	30	(1.03,5.58)

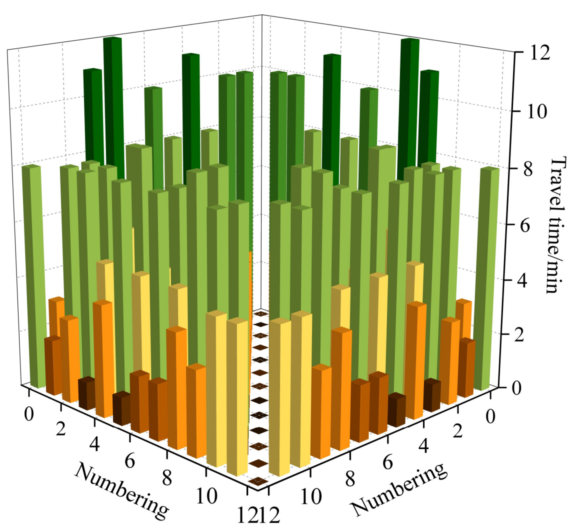


Fig. 2. Travel time between points

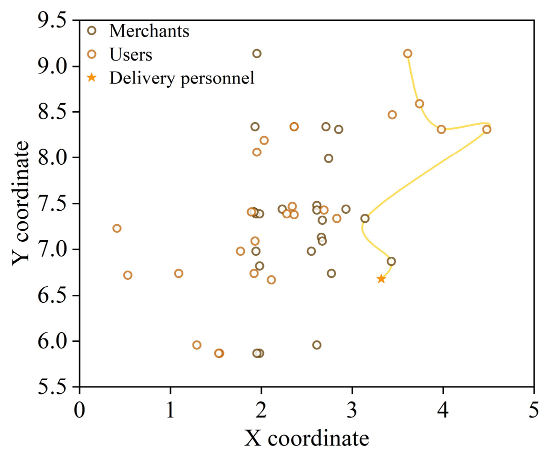
4.1.2. Experimental results. Follow the process of Ant Colony Algorithm to solve the takeaway delivery path planning problem. The setup parameters as well as the obtained results are as follows: the ant colony size is 100, the number of iterations is 250, the maximum number of orders received is 5, the deliveryman cost is 25, and the number of deliverymen is 10.

The deliveryman traveling path is shown in Table 3.

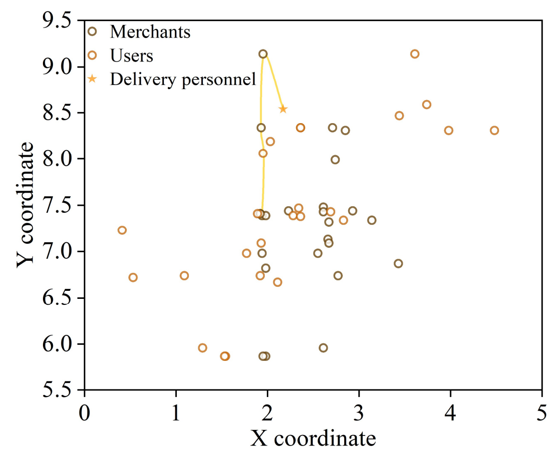
Table 3. Driving path

Delivery personnel number	Driving path
2	8→23→42→32→36→50
6	25→16→28→21→46
9	17→12→19→41→44
13	14→24→48→11→37
15	10→22→3→38→30
16	9→27→33→29→35
18	15→18→40→43→39
20	20→49→45→26
22	13→31→7→1→34
28	5→6→4→2→47

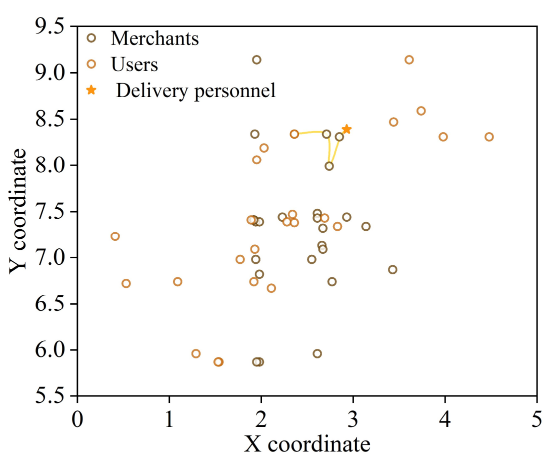
In order to more intuitively show the takeaway delivery path planning results based on ACO algorithm in this paper, the takeaway delivery path planning diagram is drawn as shown in Fig. 3, and (a)-(j) represent the delivery paths of the 10 deliverers respectively. From the figure, it can be seen that the algorithm in this paper can reasonably plan different optimal delivery routes according to the locations of merchants, users and delivery workers, thus significantly improving the delivery efficiency of takeaway delivery and thus improving the delivery quality of the takeaway platform.



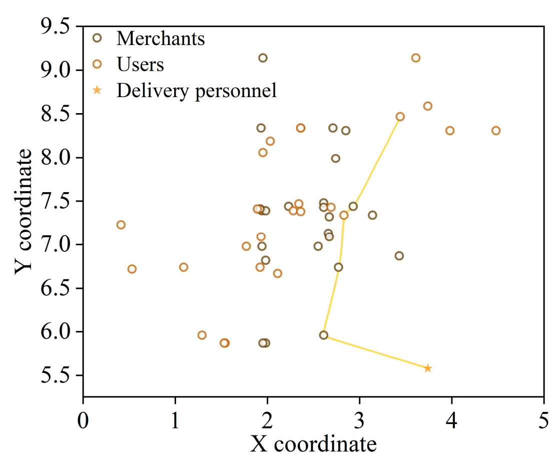
(a)Delivery personnel 2



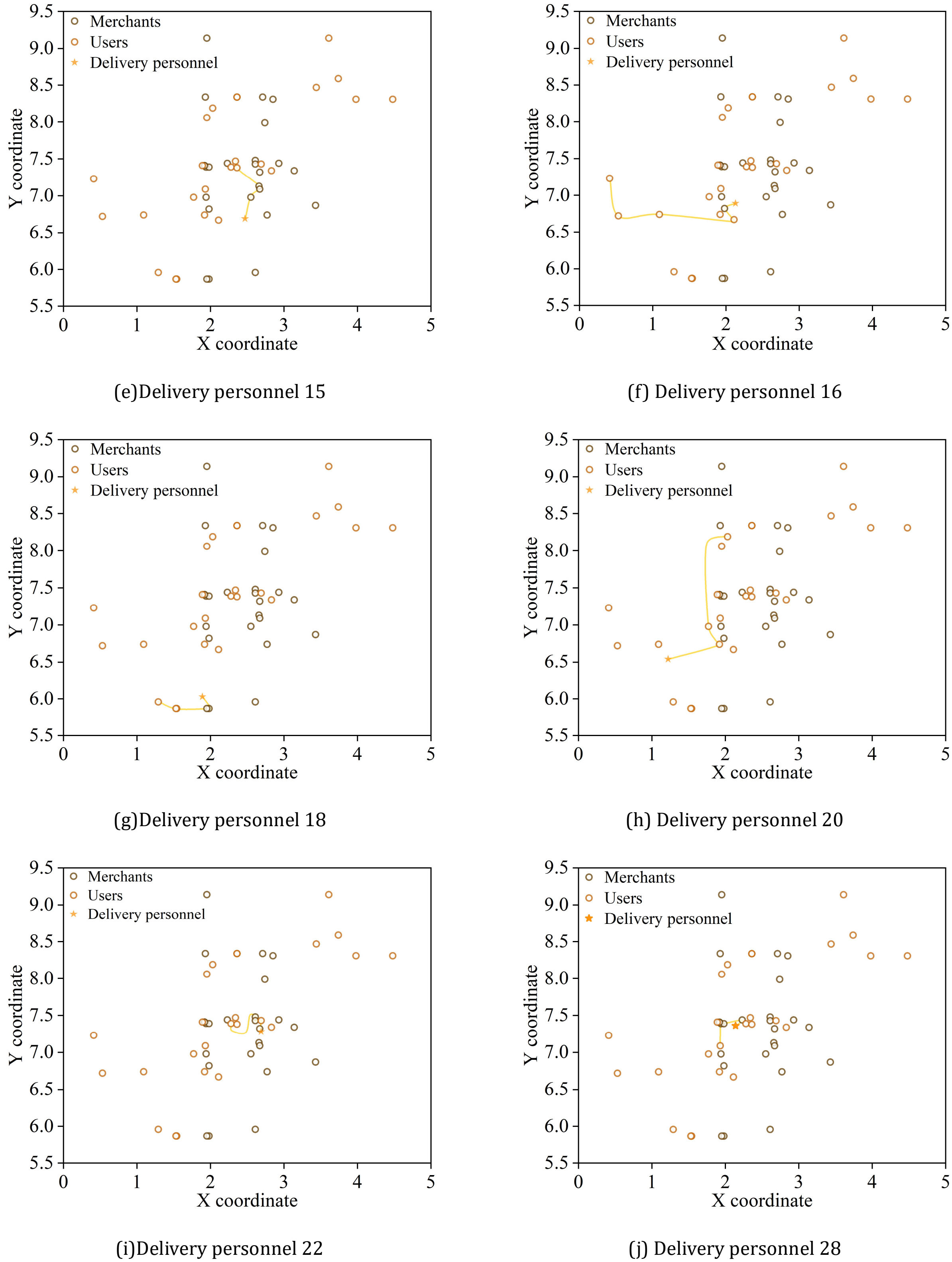
(b) Delivery personnel 6



(c)Delivery personnel 9



(d) Delivery personnel 13



(e)Delivery personnel 15

(f) Delivery personnel 16

(g)Delivery personnel 18

(h) Delivery personnel 20

(i)Delivery personnel 22

(j) Delivery personnel 28

Fig. 3. Path planning results

4.1.3. Algorithm performance analysis. By using the ant colony algorithm, the number of iterations is 250 times to get the iteration curve of the solution process of the distribution path planning problem in this paper as shown in Figure 4. From the figure, it can be seen that the results tend to stabilize at 170 iterations.

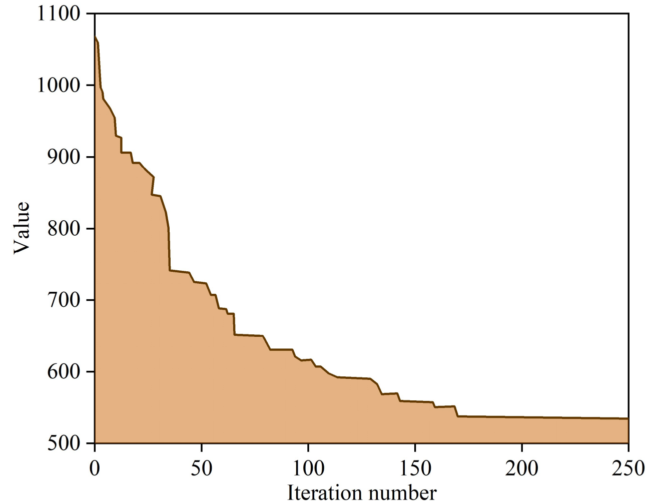


Fig. 4. The iterative curve of the algorithm

In order to further explore the solution performance of the algorithm, the path planning problem is calculated 50 times to explore the stability of the algorithm under the condition that each parameter setting is kept unchanged as set in the previous section, and the specific results are shown in Figure 5. From the figure, it can be seen that the average value of the solution results deviates from the maximum and minimum values by a small margin, which shows that the ant colony algorithm used in this paper is able to complete the path planning problem of takeaway delivery better, and the solution process is relatively stable.

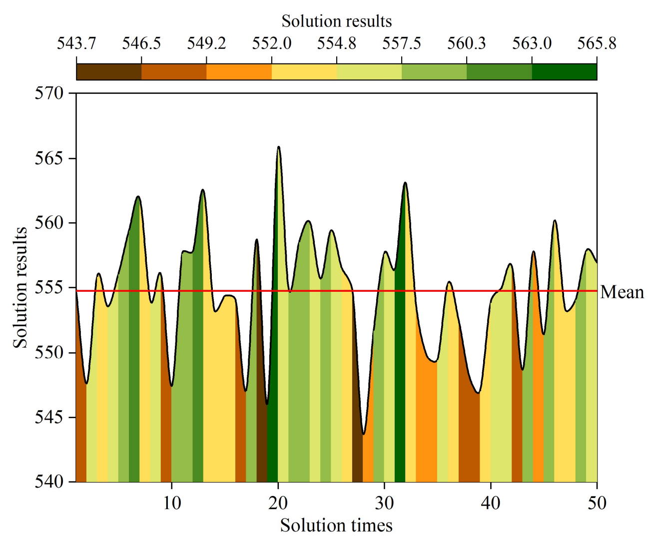


Fig. 5. The results of algorithm solving in 50 times

In summary, the takeaway delivery path planning algorithm constructed based on ant colony algorithm in this paper can practically solve the path planning problem of the deliveryman in the process of takeaway delivery, and its application in the takeaway platform can effectively realize the efficient delivery of takeaway, thus significantly improving the service quality of the takeaway platform.

4.2. Takeaway Demand Forecasting Experiment

4.2.1. Experimental data. The dataset used for the experiments in this section is the preprocessed takeout order dataset, which contains a total of 563,874 pieces of data on takeout ordering using the

MT Takeout platform in the period of January 2017~April 2023, as shown in Figure 6. Each piece of data includes a total of 12 attributes such as year, month, date, temperature, humidity, wind speed, wind direction, weather conditions and the business district where it is located, as well as the attributes of whether it is a holiday or not, and the total number of orders per unit hour. The dataset is styled randomly using sklearn's train_test_split() method, with 70% of the data being the training set and 30% of the data being the test set.

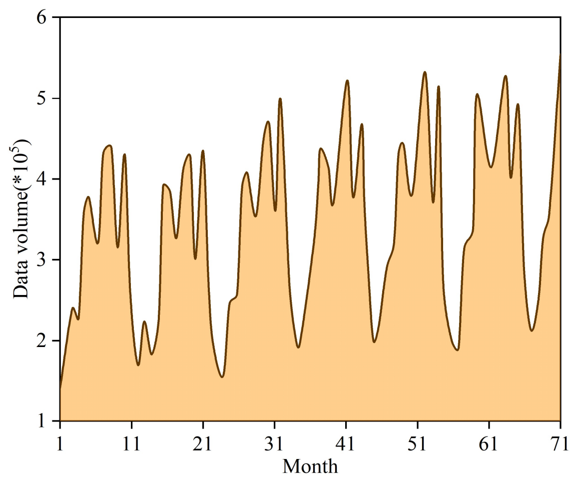


Fig. 6. Delivery order data

4.2.2. Network Initialization Learning. Using the function in the MATLAB neural network toolbox to initialize the gray neural network parameters, set the learning rate of each layer to 0.01, and then use the training dataset to train the gray neural network for a total of 150 times, and its training process is shown in Figure 7. From the grey neural network training results in the figure, it can be seen that the grey neural network convergence speed is very fast, but it quickly falls into the local optimum, and can not be further optimized for the neural network parameters, and can not obtain the optimal neural network parameters.

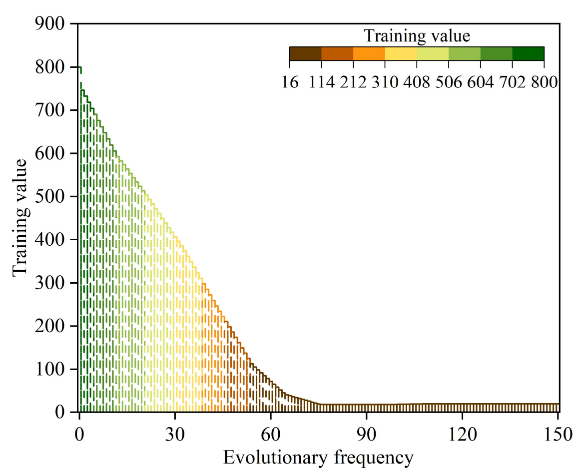


Fig. 7. The training process of grey neural network

4.2.3. Optimization of network parameters using FOA. Using Drosophila Optimization Algorithm (FOA) to optimize the grey neural network's $a, b_1, b_2, b_3, b_4, b_5$ and other 6 parameters, the population size is 50, the number of iterations to 150 times, FOA algorithm optimal individual fitness value with the number of iterations is shown in Figure 8. From the figure, it can be seen that after the FPA algorithm for the gray neural network parameter optimization, jumped out of the local optimal value, to obtain the best parameters of the network are: $a = 0.662, b_1 = 0.309, b_2 = 0.389, b_3 = 0.541, b_4 = 0.673, b_5 = 0.319$.

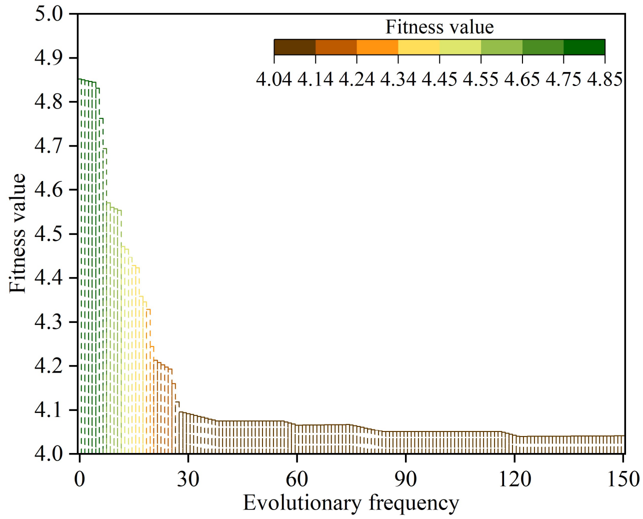


Fig. 8. FOA algorithm optimization process

4.2.4. Results and analysis. In order to show that the gray neural network model based on FOA optimization has more accurate prediction accuracy, BP neural network model and gray neural network model are used as comparison models, and each network is trained using the same training set, and the number of iterations is set to 150, and then each network is tested using the same test set, and the output of each model is shown in Figure 9. In the demand prediction of takeaway orders by each model, the prediction result of BP neural network model has the largest difference from the actual value, the gray neural network model is the second largest, and the prediction value of the gray neural network model improved by Drosophila optimization algorithm in this paper has the smallest difference from the actual value. In the 12 months of the test set, this paper's model correctly predicts the demand for takeaway orders in 10 of them, with a prediction accuracy of 83.33%. It shows that the use of the model in this paper can accurately predict the demand of users for takeaway orders in the takeaway platform, which facilitates the adoption of different service strategies for users in different demand areas, thus improving the service quality of the takeaway platform.

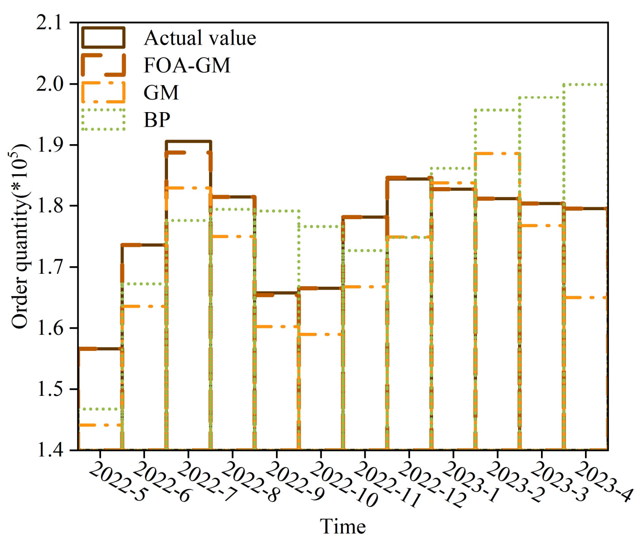


Fig. 9. Comparison of model prediction results

In order to further examine the prediction accuracy of each model, the mean square error (MSE) and mean absolute percentage of error (MAPE) were utilized as the evaluation indexes of the models. The BP neural network model, the gray neural network model and the gray neural network model improved by the Drosophila optimization algorithm in this paper were used to predict 10 times, and the MSE and MAPE of each prediction were calculated, and the results are shown in Table 4. As can be seen from the table, the MSE and MAPE of BP neural network order demand prediction results are much higher than the gray neural network model, and the comparison results show that the prediction performance of the gray neural network model is better than the BP neural network model, which can better mine the change rule of takeaway orders. At the same time, the MSE and MAPE of the improved grey neural network model in this paper are much smaller than that of the grey neural network, which shows that the parameter optimization of the grey neural network using Drosophila algorithm is successful, and it can quickly find the parameters of the global optimal neural network, which is good to avoid the defects of the grey neural network that is easy to fall into the local optimal, and it further improves the prediction accuracy of the takeaway order demand.

Table 4. The output precision parameters of each model

Prediction frequency	BP		GM		FOA-GM	
	MSE	MAPE/%	MSE	MAPE/%	MSE	MAPE/%
1	336974.05	2.47	34273.37	0.66	2297.80	0.23
2	311751.6	3.30	34117.17	0.63	1327.63	0.06
3	404884.92	2.48	44634.26	0.61	2122.46	0.10
4	336180.21	1.09	38362.57	0.54	2218.03	0.04
5	332124.40	1.79	42019.04	0.79	3210.03	0.40
6	316891.57	3.22	37435.57	0.80	1446.65	0.17
7	426034.01	2.45	38151.33	0.91	1941.79	0.23
8	407434.21	2.83	44539.10	0.62	1892.43	0.28
9	462541.78	1.76	39135.99	0.79	1762.67	0.28
10	412773.20	2.28	26581.00	0.61	2192.97	0.24

5. Conclusions and outlook

In this paper, the path planning model in the delivery process of takeout and the demand prediction model of takeout platform are constructed by using artificial intelligence computation to provide technical support for the takeout platform to improve the service quality. Combined with the experimental data collected from the takeaway platform, this paper draws the following conclusions through simulation analysis:

1) The takeaway delivery path planning model in this paper solves the takeaway delivery problem in a certain region to obtain the optimal number of delivery workers in the region as 10 in a scenario where the initial positions of merchants, users and delivery workers are known, and successfully realizes the optimal planning of delivery paths for 10 delivery workers based on the position information. The delivery efficiency is significantly improved while saving the delivery time of the deliverymen and improving their delivery efficiency, thus realizing the improvement of the service quality of the takeaway platform.

2) The optimized grey neural network model using Drosophila algorithm shows a high prediction accuracy of 83.33% in the experiment, and its MSE and MAPE values are much smaller than those of the BP neural network model and the unoptimized grey neural network model. While quickly finding the global optimal parameters of the neural network, it avoids the gray neural network falling into the local optimal situation, and improves the accuracy of the prediction of takeaway order demand. Using this model can accurately predict the takeout demand of users in the platform, which is convenient for

the takeout platform to formulate different service strategies and resource scheduling strategies according to the user's demand, and further improve the service quality of the takeout platform.

There are also some shortcomings in this study. For example, during the construction of the path planning model, although a variety of factors are considered, the actual situation may be more complex, and the accuracy and generalization ability of the model need to be further improved. In terms of data collection, the completeness and accuracy of some of the data are affected to some extent due to the sensitivity of the data and the difficulty of obtaining them. Future research can be carried out in the following aspects: first, further optimize the model by introducing more real-time data and complex factors to improve the performance of the model; second, strengthen the research on data security and privacy protection, and expand the amount of data researched in this paper within the legal scope.

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