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Route Planning for Chain Restaurants With Improved Delivery Mode Using an Adaptive Genetic Algorithm

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ABSTRACT With the popularization of logistics technology and the improvement of people's living standards, the number of chain restaurants with delivery service is increasing continuously due to the convenient service and special discounts. However, the inappropriate management mode and delivery delays often lead to high delivery cost, especially during the peak meal period. Therefore, to solve the problems, two delivery modes, Modern Delivery Mode of Chain Restaurants (MDMCR) and Improved Delivery Mode of Chain Restaurants (IDMCR) were first proposed. IDMCR is an one-stage approach to directly solve the delivery routing problem of multiple branches. Furthermore, we presented an adaptive genetic algorithm for delivery of chain restaurants (AGA-DCR) specifically for IDMCR, which adjusts adaptively the traditional crossover and mutation operations to the fitness of individual and population, therefore, local optimal is avoid. The experiments were conducted with the same dataset to compare different approaches. The results demonstrated that AGA-DCR avoided falling into the local optimal while improved the quality of the solution. Moreover, IDMCR combined with AGA-DCR achieved the best performance, reducing the delivery delay cost by 56.2% compared to MDMCR with GA. Additionally, the optimal delivery routes for chain restaurants were visualized to provide a reference solution for the practical applications.

INDEX TERMS Adaptive genetic algorithm, chain restaurants delivery, delivery mode, vehicle routing.

I. INTRODUCTION

Chain restaurants such as McDonald's, Pizza Hut and KFC provide delivery services through online ordering in recent years. These restaurants usually have many branches and delivery staff within a certain serving range. Consumers who choose to order food online can enjoy not only the convenient service, but also the special discounts [1]. This makes the chain restaurants receive widespread attention.

The delivery service of chain restaurants is a part of Multi-Depot Vehicle Routing Problem (MDVRP). In this mode, the restaurant system or takeout platform automatically receive orders and obtain order information, such as location, demand and delivery time, etc. The delivery staff can be a full-time employee who belongs to the restaurant, a part time biker who belongs to the crowd sourced logistics company or a full-time biker who serves the takeaway platform. In this study, suppose everyone orders food online and all their orders are sent to the restaurant system, each delivery staff completes the delivery task in sequence according to the planning. Each branch of the chain restaurants has its own delivery staff who is formal employee and only serves this branch. In the past research, scholars like to turn MDVRP into SDVRP (Single Depot Vehicle Routing Problem), if this is the case, then the task arrangement of the branch during the peak meal period is unreasonable. For example, there are too many customers around the one of chain restaurants, it maybe cause serious delivery delayed phenomenon so that improve the total delivery cost. Therefore, in order to propose the optimized route planning for chain restaurants, the original delivery mode is improved and the corresponding mathematical models is

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established. The original and improved delivery modes are shown as follows:

1) MODERN DELIVERY MODE OF CHAIN RESTAURANTS (MDMCR):

The restaurant platform selects the branch nearest to the customer for distribution. The delivery routing problem in this mode belongs to the Single-Depot Vehicle Routing Problem with Time Windows (SDVRPTW).

2) IMPROVED DELIVERY MODE OF CHAIN RESTAURANTS (IDMCR):

The platform collects customer orders and assigns tasks together in a short period of time, making full use of the delivery staff of the branches in the region to complete the delivery collaboratively, and plans the delivery route through the intelligent algorithm. The delivery routing problem in this mode belongs to the Multi-Depots Vehicle Routing Problem with Time Windows (MDVRPTW).

This paper aimed to deal with the delivery routing problem for chain restaurants, and the main contributions are as follows. (1) we established two mathematical models, MDMCR and IDMCR, aiming to solve the problem of inappropriate management mode in the chain restaurants. (2) Considering that GA may easily fall into the local optimal trap due to the simultaneous consideration of multiple constraints, such as multi-depots and time windows, we proposed an Adaptive Genetic Algorithm for Delivery of Chain Restaurants (AGA-DCR) especially for IDMCR. In AGA-DCR, each individual consists of a delivery staff sequence and a delivery route sequence, and the adaptive method is used to adjust the crossover and mutation probability through exponential function relation. (3) We conducted experiments to verify the performance of our approach, and the results demonstrated that AGA-DCR avoided falling into the local optimal while improved effectively the performance. And the optimal delivery routes for chain restaurants were visualized to provide a reference for the practical path planning.

II. LITERATURE REVIEW

A. MULTI-DEPOTS VEHICLE ROUTING PROBLEM (MDVRP)

The previous researches on MDVRP mainly focused on the improvement of the algorithm and have shown the transformation from the traditional heuristic algorithm to the modern heuristic algorithm. Tillman *et al.* [2] proposed the MDVRP solution which assigns customer points to the nearest depots and then introduces the heuristic algorithm for route planning. Wren *et al.* [3] proposed a scanning algorithm to solve MDVRP with 176 customer points and 2 depots. Giosa *et al.* [4] assigned customers to depots according to their own characteristics, thereby converting multiple depots to single-vehicle VRP. R Fitriana *et al.* [5] proposed improvements to the depot distribution of each destination and determined the distribution of the depot to the best destination, so as to achieve the distance and time most effectively. El Midaoui Marouane *et al.* [6] applied MDVRP to medical logistics, making hospitals and centralized pharmacies become customers and warehouses respectively, and implemented GA to solve the NP hard problem. Taking the customers' preferences and distribution cost into account, Calvet *et al.* [7] combined statistical techniques and metaheuristics to maximize companies' benefits. Mahmud *et al.* [8] used GA to divide MDVRP into VRP with a single depot using border genes of GA and then solved them. Ma *et al.* [9] focused on the MDVRP for hazardous materials transportation, considering the energy consumption and transportation risk especially with a two-stage approach and hybrid multi-objective genetic algorithm, to solve the MDVRP in their model. Zhu x *et al.* [10] proposed a heuristic algorithm combining variable neighborhood search algorithm (VNS) and space saving heuristic algorithm (SSH) to solve the multi-site capacity constrained electric vehicle routing problem (2l-MDSVRP) composed of two-dimensional weighted terms. When studying the multi-depot split delivery vehicle routing problem (MDSVRP). Lim H P *et al.* [11] adopts the mixed integer programming (MIP) model, improves the GA, and proposes a new GA with two-dimensional chromosome representation. Shi *et al.* [12] Studied MDVRP in garbage collection problem by using two-stage method, and optimized the model by using sector combination optimization (SCO) algorithm. However, it does not take into account the time window and service cost

B. MULTI-DEPOTS VEHICLE ROUTING PROBLEM WITH TIME WINDOWS (MDVRPTW)

Scholars have begun to study the vehicle routing optimization under various constraints since the end of the 20th century. Among them, MDVRPTW, which has the constraints of multiple depots and time window, has more detailed settings and is closer to real applications of logistics. Mir Ehsan *et al.* [13] proposed a variable tabu neighborhood search (VTNS) algorithm to solve MDVRP, MDVRPTW and multi-base open vehicle routing problem. However, the efficiency is reduced when multiple terminals send a heterogeneous fleet to transport goods between the retailer's distribution center and the customer's location. Bae [14] used the Nearest Neighbor Heuristics (NNH) to decompose MDVRPTW into multiple Single Depot Vehicle Routing Problem (SDVRPTW), and then solved the decomposed problems. Finally, the optimal performance of GA was verified. Sazonov V *et al.* [15] established a multi-agent system with the interaction of trucks, warehouses and orders to solve the MDVRPTW. To limit the intensity of negotiations, a Delaunay triangulation-based scene structure was proposed. Vidal *et al.* [16] considered some constraints and designed a hybrid genetic algorithm to solve MDVRPTW. Karakati S [17] proposed a genetic algorithm to solve the capacitive MDVRPTW. The comparison of the partial studies mentioned above is listed in Table 1.

TABLE 1. Comparison of the factors considered in the models of MDVRP.

Studies	Two-stage Approach	One-stage Approach	Time Windows	Service Time	Distance	Fixed Time
Tillam *et al.* [2]	√	-	-	-	√	√
Giosa *et al.* [4]	√	-	√	-	√	-
Lim *et al.* [11]	-	√	-	-	√	-
Mahmud *et al.* [8]	√	-	-	-	√	-
Ma *et al.* [9]	√	-	-	-	√	-
Shi *et al.* [12]	√	-	-	-	√	-
Bac *et al.* [14]	√	-	√	√	√	-
Vidal *et al.* [16]	-	√	√	√	√	-
MDMCR (this study)	√	-	√	√	√	√
IDMCR (this study)	-	√	√	√	√	√

C. HEURISTIC ALGORITHM FOR VRP

VRP is one of the NP-hard problems, and heuristic algorithms have proven to be effective ways to solve it. Among those heuristic algorithms, genetic algorithms and improved genetic algorithms have been extensively introduced into VRP due to its fast convergence and stability [18], [19]. Wang Y [20] proposed a modified non dominant sorting genetic algorithm-II (m-nsga-ii), which can locate logistics facilities, allocate customers and optimize vehicle routing network at the same time, so as to solve the double echelon location routing problem in time window. Asghar and Hosseinabadi [21] combined gravity simulation based local search (gels) and GA to solve the capacitive vehicle distribution problem (CVRP). Belka and Godlewski [22] optimized the VRP Problem by studying the impact of updating the customer's geographical location on the distance matrix. Xia and Wei [23] proposed a hybrid algorithm named dsmo-ga to solve the vehicle routing problem (VRPSD) in which customer requirements follow a known probability distribution. For the vehicle routing problem with backhaul, Daham *et al.* [24] developed an evolutionary genetic algorithm which is tested to be efficient for solving large scale problems. And the result shows that combining linehaul and backhaul cases saves delivery cost and vehicles. Focusing on the research of the last mile, Zhen L *et al.* [25] proposed a hybrid particle swarm optimization algorithm and hybrid genetic algorithm.

As the chain restaurants increase in recent years, people payed more attention to their delivery route planning. According to the previous researches on VRP, the delivery routing problem of chain restaurants belongs to MDVRPTW, which aims to deliver foods to the customers with time window at the least delivery cost. MDMCR is to use the two-stage approach to plan the route according to the researches of most scholars [9], that is, to allocate customers to the branch according to a certain method, to transform MDVRPTW into SDVRPTW, and then to plan the delivery route planning through algorithms. In fact, the geographical location of branches and customers is scattered irregularly. At the same time, the customer time windows are intensive during the peak meal period, so there are higher requirements for the efficiency of delivery service. After investigating the actual delivery situation, for several large takeout platforms in China, as long as delivery staff arrived at customer points not on time, the chain restaurants directly compensate the consumer for suitable amount of money [26]. The timeout penalty cost is one of constraints and one element in the total delivery cost to reduce the occurrence of the delayed phenomenon and achieve the purpose of reducing the total delivery cost. It is found that the quality of the solution of the two-stages method is not better than the direct method in MDVRP [27]. Therefore, it is proposed to use IDMCR to serve directly all the customers in a certain space. The literature has proved that heuristic algorithm is more suitable for the problem solving in this scenario than the precise algorithm. IDMCR proposed that is solved by heuristic algorithm AGA-DCR, which considering the timeout penalty cost, fixed cost and distance cost, to optimize the delivery route planning.

III. MATHEMATICAL FORMULATION

A. MDMCR

MDMCR is described as follows: According to the distance of different orders, the orders are assigned to the corresponding branches for delivery service, so the MDVRPTW is converted to several SDVRPTW sets, and then the optimal solutions of separated SDVRPTW are accumulated to form the overall optimal solution. From the literature reviewed, there are two main allocation methods: the shortest distance allocation method and the boundary allocation method. Branches of chain restaurants utilize the shortest distance allocation method to assign customers to the nearest branch. Assumed that the constraints are as follows:

1) The location of each branch is fixed; the delivery staff departs from each branch and then serves each customer point in order, and finally returns to the original branch after the delivery task is completed; all delivery staff have the same driving speed and unit distance cost;
2) The demand and location information of each customer point are known; it's assumed that the goods in each

TABLE 2. Parameters and variables in MDMCR.

Notations	Description
Z_r	The objective function of the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
M_r	The total customers point of the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
K_r	The total available delivery staff of the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
P_l	Timeout penalty cost per unit
P_f	Fixed cost unit per delivery staff
P_d	Cost per unit distance
Q	Maximum load of delivery staff
$[e_i^r, l_i^r]$	Waiting window time of $i-th$ customer point in the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
a_i^r	Service time of $i-th$ customer point in the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
g_i^r	Demand of $r-th$ customer point in the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
$d_{i\ j}^r$	Delivery distance from point i to j in the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
$r_{i\ j}^r$	Delivery time from point i to j in the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
t_j^r	Arrival time of point j when the delivery staff who belongs to the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
t_i^r	Arrival time of point i when the delivery staff who belongs to the $r-th$ branch, $r \in \{1,2,\ldots,R\}$
$x_{i,j}^{k,r}$	When $x_{i,j}^{k,r}=1$, delivery staff k from point i to point j who belongs to the $r-th$ branch; $x_{i,j}^{k,r}=0$,otherwise; i , j in T_r , $i \neq j$, $k \in \{1,2,\ldots,K_r\}$, $r \in \{1,2,\ldots,R\}$

branch are usually enough for the costumers, and the number of delivery staff sent by each branch cannot exceed the total number of delivery staff in the branch;
3) The time window of each customer point is different, and the service time varies accordingly. Timeout penalty is incurred when delivery staff arrives after the time window. When the delivery staff arrives at the customer point in advance, the staff should wait until the time window starts;
4) The demands of customer points on the delivery route of each delivery staff arranged by the branch are not greater than the maximum load;
5) The need of each customer point should be met and served only once by a delivery staff;
6) The road is unobstructed, without special situations such as traffic jam and cancellation of orders;
7) The vehicle used by the delivery staff is an electric bike, and the power consumption cost is included in the distance cost;
8) The salary of the delivery staff doesn't change with the quantity of delivery, so it is also included in the fixed cost.

There are R branches in the area, and the distance between the customer point and each branch is measured. According to the nearest distance delivery method, the customer point is assigned to the nearest branch for service. The model of MDMCR is established as follows. Assuming that k is one of the delivery staff in the r branch, where $k \in \{1, 2, \ldots, K_r\}$, and D_r is the set of customer points, where $D_r = \{1, 2, \ldots, M_r\}$. T_r is the total set and $T_r = 0 \cup D_r = \{0, 1, \ldots, M_r\}$where 0 represents no deZlivery tasks in r branch; t_j^r is the arrival time of customer point j when delivery staff who belongs to the $r - th$ branch and $t_j^r = t_i^r + a_i^r + \max\left(e_i^r - t_i^r, 0\right) + t_{i,j}^r$. The relevant variables and parameters of the model are shown in Table 2.

The objective function of total delivery cost:

$$Z = \sum_{r=1}^{R} \min Z_r, \quad r \in \{1, 2, \ldots, R\} \tag{1}$$

$$Z_r = \min\left(P_d \cdot \sum_{k=1}^{K_r}\sum_{i=0}^{M_r}\sum_{j=0}^{M_r} d_{i,j}^r \cdot x_{i,j}^{k,r} + P_r \cdot \sum_{j=1}^{M_r} \max\left(t_j^r - l_j^r, 0\right) + P_f \cdot \sum_{k=1}^{K_r}\sum_{j=1}^{M_r} x_{0,j}^{k,r}\right) \tag{2}$$

$$\text{S.T.} \sum_{k=1}^{K_r}\sum_{j=1}^{M_r} x_{0,j}^{k,r} \le K_r \tag{3}$$

$$\sum_{j=1}^{M_r} x_{0,j}^{k,r} = \sum_{j=1}^{M_r} x_{0,j}^{k,r} \le 1, \quad k \in \{1, 2, \ldots, K_r\} \tag{4}$$

$$\sum_{k=1}^{K_r}\sum_{j=0}^{M_r} x_{i,j}^{k,r} = 1, \quad i \in D_r \tag{5}$$

$$\sum_{k=1}^{K_r}\sum_{i=0}^{M_r} x_{i,j}^{k,r} = 1, \quad i \in D_r \tag{6}$$

$$\sum_{i=0}^{M_r}\sum_{j=1}^{M_r} g_j^r \cdot x_{i,j}^{k,r} \le Q, \quad K \in \{1, 2, \ldots, K_r\} \tag{7}$$

Equation (1) is the objective function of the total delivery cost which is the sum of the delivery cost of all branches. Equation (2) is the objective function of $r - th$ branch which is the sum of its distance cost, timeout penalty and fixed cost. The mathematical model of constraint condition is as follows: Equation (3) is the number of delivery staff sent by each branch, which is less than the total number of delivery staff available. Equation (4) means that all delivery staff depart from the branch which they belong to and return to. Equation (5) and (6) indicate that each customer point only be served once by a delivery staff. Equation (7) shows that the total demand of customer points should not be greater than the maximum load of delivery staff.

B. IDMCR

Because MDMCR does not adopt centralized scheduling management mode in logistics management, which easily leads to uneven distribution of orders even delivery delays. In order to solve this problem, we changed the distribution management mode into an original mode, Improved Delivery Mode of Chain Restaurants (IDMCR), which takes each branch of the chain restaurant as multiple sites, uses the heuristic algorithm to uniformly schedule the distribution tasks of all customer points of each branch. In contrast to MDMCR, which focus only on decreasing delivery cost of one branch, IDMCR concentrates on minimizing the total delivery cost of all the branches.

In addition to the assumptions (1)-(8) mentioned above, there are still two another constraints as follows:

9) The summed total delivery cost of branches are considered, the delivery staff from all branches are assigned with the delivery tasks globally;
10) Each delivery staff has its own branch to serve and should return to its own branch after completing the task.

The mathematical model of IDMCR is established as follows. Assuming that V is the set of branches and $V = \{1, 2, \ldots, M\}$, D is the set of customer points, $D = \{M+1, M+2, \ldots, M+N\}$; T is the total set and $T = V \cup D = \{1, 2, \ldots, M+N\}$; t_j is the delivery staff's arrival time of customer point j, and $t_j = t_i + a_i + \max(e_i - t_i, 0) + t_{i,j}$. The relevant variables and parameters of the model are shown in Table 3.

The objective function of total delivery cost is as follows:

$$Z = \min\left(P_d \cdot \sum_{m=1}^{M}\sum_{k=1}^{K_m}\sum_{i=1}^{M+N}\sum_{j=1}^{M+N} d_{i,j} \cdot x_{i,j}^{m,k} + P_l \cdot \sum_{j=M+1}^{M+N} \max\left(t_j - l_j, 0\right) + P_f \cdot \sum_{m=1}^{M}\sum_{k=1}^{K_m}\sum_{j=1}^{M+N} x_{m,j}^{m,k}\right) \tag{8}$$

$$\text{S.T.} \sum_{k=1}^{K_m}\sum_{j=M+1}^{M+N} x_{i,j}^{m,k} \le K_m, \quad i = m \in V, \tag{9}$$

$$\sum_{j=M+1}^{M+N} x_{i,j}^{m,k} = \sum_{j=M+1}^{M+N} x_{j,k}^{m,k} \le 1, \quad i = m \in V, \; k \in \{1, 2, \ldots K_m\}, \tag{10}$$

$$\sum_{m=1}^{M}\sum_{k=1}^{K_m}\sum_{j=1}^{M+N} x_{i,j}^{m,k} = 1, \quad i \in D \tag{11}$$

TABLE 3. Parameters and variables in IDMCR.

Notations	Description
K_m	The total number of each branch available delivery people, $m \in V$
P_l	Timeout penalty cost per unit
P_f	Fixed cost unit per delivery staff
P_d	Cost per unit distance
Q	Maximum load of delivery staff
$[e_i, l_i]$	Waiting window time of $i-th$ customer point, $i \in D$
a_i	Service time of $i-th$ customer point, $i \in D$
g_i	Demand of $i-th$ customer point, $i \in D$
$d_{i,j}$	Delivery distance from point i to j, $i \in T, j \in T$
$r_{i,j}$	Delivery time from point i to j, $i \in T, j \in T$
t_j	The time of when delivery staff arrived the point j, $j \in T$
t_i	The time of when delivery staff arrived the point i, $i \in T$
$x_{i,j}^{m,k}$	When $x_{i,j}^{m,k} = 1$, delivery staff k from point i to point j who belongs to the $m-th$ branch; $x_{i,j}^{m,k} = 0$;otherwise; i, j in T, $i \ne j$, $k \in 1, 2, \ldots, K_m$

$$\sum_{m=1}^{M}\sum_{k=1}^{K_m}\sum_{i=1}^{M+N} x_{i,j}^{m,k} = 1, \quad j \in D \tag{12}$$

$$\sum_{i=1}^{M+N}\sum_{j=M+1}^{M+N} g_j \cdot x_{i,j}^{m,k} \le Q, \quad m \in V, \; k \in \{1, 2, \ldots, K_m\} \tag{13}$$

$$\sum_{j=1}^{M} x_{i,j}^{m,k} = \sum_{j=1}^{M} x_{j,i}^{m,k} = 0, \quad i = m \in V, \; k \in \{1, 2, \ldots, K_m\} \tag{14}$$

$$\sum_{j=M+1}^{M+N} x_{m,j}^{m,k} \le 1, \quad m \in V, \; k \in \{1, 2, \ldots, K_m\} \tag{15}$$

Among them, Equation (8) is the objective function of IDMCR which is the sum of distance cost, timeout penalty cost and fixed cost. The constraint conditions of this mode: Equation (9) represents that the number of delivery staff sent by each branch cannot exceed the total number of delivery staff available in the branch. Equation (10) shows that all delivery staff set off from the corresponding branch and shall finally return to the branch. Equation (11) and (12) indicate that each customer point only needs one delivery staff to serve once. Equation (13) means the total demand for the service points of each delivery staff should not be greater than the maximum carrying capacity. Equation (14) indicates that the delivery staff don't depart from the branch to another branch. Equation (15) indicates the delivery staff has the possibility of participating in task delivery.

IV. ADAPTIVE GENETIC ALGORITHM FOR DELIVERY OF CHAIN RESTAURANTS (AGA-DCR)

Genetic Algorithm (GA), which is a heuristic algorithm simulating the process of natural selection, has strong robustness and faster searching capabilities. However, GA may easily falls into local optimal [28], [29] since it is prone to premature control. Therefore, an Adaptive Genetic Algorithm for Delivery of Chain Restaurants (AGA-DCR) is proposed. In AGA-DCR, each individual is set to contain two gene sequences, a delivery staff sequence and a route sequence. These two sequences can represent different delivery schemes. The adaptive method can also adjust the probabilities of crossover and mutation dynamically to prevent from jumping into the local optimal.

A. ENCODING AND INITIALIZATION OF INDIVIDUALS

1) DELIVERY STAFF SEQUENCE (DSS)

There is only one delivery route for one delivery staff and each customer point can only be served by one delivery staff. The customer points and delivery staff are therefore assigned numbers. The total number of the available delivery staff is calculated as shown in (16).

$$K_{sum} = \sum_{m=1}^{h} K_m, \tag{16}$$

The delivery staff sequence is numbered according to the serial number of the branch to which each delivery staff belongs as shown in Fig. 1. The serial number in each sequence represents the branch to which each delivery staff belongs. DSS, which is one of the gene sequences in each individual in AGA-DCR, will be used in selection, mutation, and crossover operations in the following steps.

$$[\overbrace{1,\ldots,1}^{K_1},\ \overbrace{2,\ldots,2}^{K_2},\ldots,\ \overbrace{M,\ldots,M}^{K_m}]$$

FIGURE 1. Delivery staff sequence (DSS).

2) ROUTE SEQUENCE (RS)

The number of the customer points N is obtained in AGA-DCR for initial number to form a sequence of customer points [1, 2,..., N]. It represents the order in which the delivery tasks are to be assigned. RS is another gene sequence contained in each individual in AGA-DCR, participating in select, mutation, and crossover operations in the following steps.

B. TASK ASSIGNMENT AND FITNESS CALCULATION CALCULATION

The fitness in AGA-DCR determines whether an individual can be retained during the iteration process. According to the individual's DSS and RS, the delivery task is arranged and the fitness is calculated. The steps are as follows:

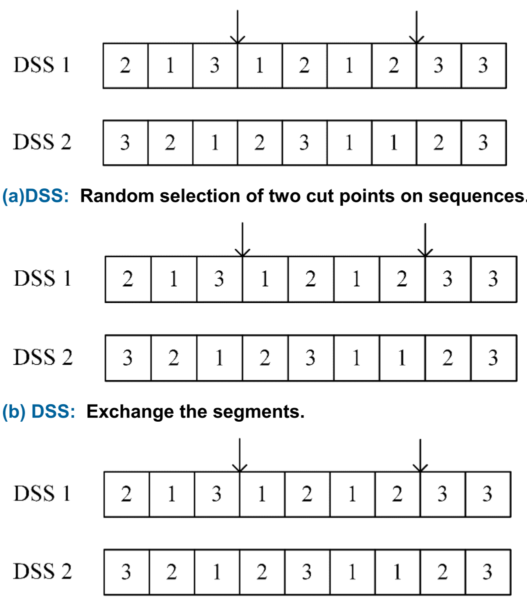
1) For the $i-th$ individual in the population, a delivery staff is selected to be assigned to a delivery task in its DSS, and the customer points are selected as many as possible (but not exceeding the maximum capacity of the vehicle) to deliver;
2) All customer points in the RS are judged whether they have been scheduled for delivery or not. If not, return to step (1), otherwise go to step (3);
3) After the task assignment is completed, the delivery plan of the $i-th$ individual in the population will be generated and input in Equation (4) to obtain its total delivery cost;
4) The fitness of the $i-th$ individual is Calculated, as $f_i = \frac{1}{z_i}$.

C. OPERATION SELECTION

In AGA-DCR, the selection parameter P_s $(0 < P_s < 1)$ is set and the selection operation is carried out by the combination of roulette-wheel selection [30] and selection parameter P_s. According to the fitness of the individual, $S \cdot P_s$ (S is the size of population) individuals are selected from the parent population for the adaptive crossover and mutation operations, and then put into the next generation of the population. While the unselected individuals, $S \cdot (1 - P_s)$ do not participate in the above operations and directly remain in the next generation of population.

D. ADAPTIVE CROSSOVER OPERATION

In AGA-DCR, the crossover method is Partially Mapped Crossover (PMX) [31]. The crossover probability P_c is set, which means that the individuals have the probability of P_c to crossover. The PMX procedures of DSS are as shown in Fig. 2, and the PMX procedures of RS are shown in Fig. 3.



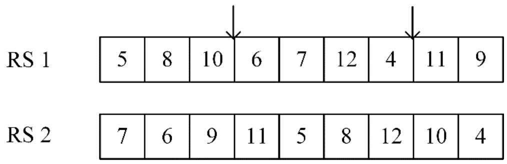
(a)DSS: Random selection of two cut points on sequences.

(b) DSS: Exchange the segments.

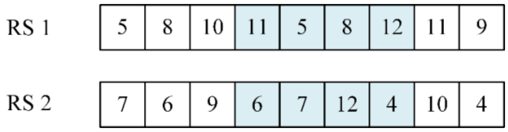
(c) DSS: Partial mapping for eliminating conflicts.

FIGURE 2. The PMX procedures of DSS.

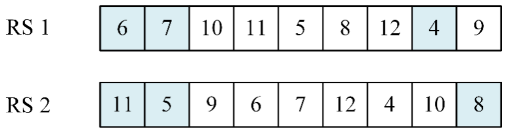
Moreover, the crossover probability P_c will be adaptively adjusted through the exponential function according to the



(a) RS: Random selection of two cut points on sequences.



(b) DSS: Exchange the segments.



(c) DSS: Partial mapping for eliminating conflicts.

FIGURE 3. The PMX procedures of RS.

relationship between the fitness of the individual and the population, as shown in (17).

$$P_c = \begin{cases} \beta_1, & f_i < \overline{f} \\ \beta_1 \cdot \beta_2^{-\frac{f_i - \overline{f}}{f_{\max} - \overline{f}}}, & f_i \geq \overline{f}, \end{cases} \tag{17}$$

where f_i is the fitness of the $i-th$ individual in the population, $f_{\max}$ is the maximum fitness of the individuals in the population, $\overline{f}$ is the average fitness of the individuals in the population, and β_1, β_2 are preset parameters of the adaptive crossover operation.

1) When $f_i > \overline{f}$, it indicates that the fitness of the $i-th$ individual is higher than the average of the population fitness; higher individual's fitness means that it's not necessary to carry out too many cross operations to obtain new sequences, but necessary to properly retain the original individual's gene sequence. The individuals' crossover with lower possibility is more likely to retain high-quality individuals through exponential function.
2) When $f_i < \overline{f}$, it indicates that the fitness of the $i-th$ individual is lower than the average of the population fitness; at this time, P_c will be set to the value of the preset parameter β_1 so as to make the inferior individual have more possibility to change itself by crossover.
3) When $f_i = \overline{f}$, f_i reaches the maximum fitness of the population, so the crossover operation is carried out with the minimum probability in order to retain more high-fitness individuals.

The relationship between crossover probability P_c and fitness of an individual f_i in the traditional adaptive algorithm is as shown as line 1 [32] and line 2 [33] in Fig. 4, which is a liner relationship between P_c and f_i.

Compared with line 1, the adaptive adjustment method proposed in this paper allows the individual with maximum

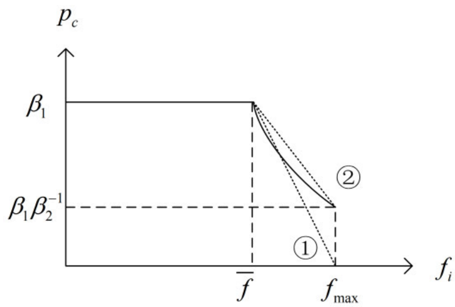


FIGURE 4. Curve of adaptive adjustment method of crossover.

fitness in the population also has a small probability to crossover, so as to avoid falling into the local optimal solution; compared with line 2, the proposed adaptive adjustment method belongs to the concave function, and its crossover probability is reduced, so that the high-quality individual is more likely to be retained.

E. ADAPTIVE MUTATION OPERATION

In AGA-DCR, according to the mutation probability P_m, the individual will have the probability of P_m to mutate its chromosomes through the 2-opt method [34], as shown in Fig. 5 and Fig.6.

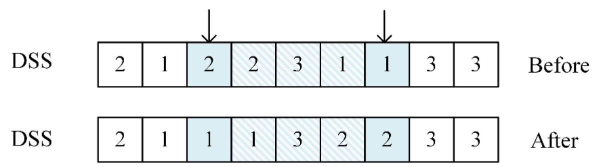


FIGURE 5. DSS: sequence mutation through 2-opt method.

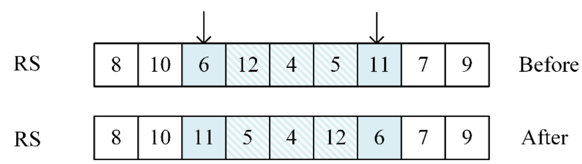


FIGURE 6. RS: sequence mutation through 2-opt method.

Moreover, the mutation probability P_m is adaptively adjusted according to the relationship between the fitness of the individual and the fitness of the population, as illustrated in (18).

$$P_m = \begin{cases} \alpha_1, & f_i < \overline{f} \\ \alpha_1 \cdot \alpha_2^{-\frac{f_i - \overline{f}}{f_{\max} - \overline{f}}}, & f_i \geq \overline{f}, \end{cases} \tag{18}$$

where f_i is the fitness of the $i-th$individual in the population, and $f_{\max}$ is the maximum fitness of the individuals in the population, and $\overline{f}$ is the average fitness of the individuals in the population, and α_1, α_2 are preset parameters of the adaptive mutation operation.

1) When $f_i > \overline{f}$, it indicates that the fitness of the $i-th$ individual is higher than the average of the population

fitness; higher individual's fitness means that it's not necessary to carry out too many cross operations to obtain new sequences, but it's necessary to properly retain the original individual's gene sequence. The individuals mutated with lower possibility are more likely to retain high-quality individuals through exponential function.

2) When $f_i < \overline{f}$, it indicates that the fitness of the $i - th$ individual is lower than the average of the population fitness. At this time, P_m will be set to the value of the preset parameter α_1 so as to make the inferior individual have more possibility to change by mutation.
3) When $f_i = \overline{f}$, f_i reaches the maximum fitness of the population, so the mutation operation is carried out with the minimum probability $\alpha_1 \cdot \alpha_2^{-1}$ in order to retain more high-fitness individuals.

The relationship between mutation probability P_m and fitness of an individual f_i in the traditional adaptive algorithm is as shown as line 1 [32] and line 2 [33] in Fig. 7, which is a liner relationship between P_m and f_i.

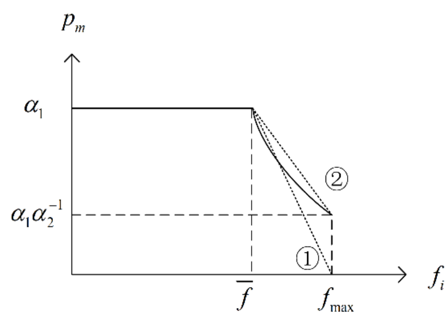


FIGURE 7. Curve of adaptive adjustment method of mutation.

Compared with line 1, the adaptive adjustment method we proposed allows the individual with maximum fitness in the population also to have a small probability to mutation, avoiding falling into the local optimal solution. Compared with line 2, our method adopts the concave function, and its mutation probability is reduced, so the high-quality individual is more likely to be retained.

To sum up, we obtain the flow chart of AGA-DCR, as shown in Fig. 8.

V. EXPERIMENTS

A. DATASET AND EXPERIMENTAL ENVIRONMENT SETTINGS

As shown in Table 4, three branches are set to serve 25 customer points within the specified time period. Each customer point has its own time window, service time and demand. The points 1,2,3 are the branches, and points 4-28 are the customer points.

For the sake of simplicity, we assume as follows.

1) The delivery distance between the two points is 1.2 times of the straight-line distance;
2) The fixed cost per delivery staff is CNY 2, and the cost per unit distance is 1.5 CNY/Km;

TABLE 4. Delivery center and customer point information.

No.	X Axis/m	Y Axis/m	Demand /Kg	Time Window/min	Service Time/min
1	5040	5880	-	[0,-]	-
2	4200	7200	-	[0,-]	-
3	3600	6000	-	[0,-]	-
4	4920	5880	10	[15.1,18.1]	2
5	4200	2040	7	[4,7]	2
6	6600	5400	13	[10.6,13.6]	2
7	6600	2400	19	[13.9,16.9]	2
8	1800	3600	26	[2.4,5.4]	2
9	3000	3600	3	[8.9,11.9]	2
10	2400	6000	5	[7.1,10.1]	2
11	1200	5160	9	[8.5,11.5]	2
12	6600	7200	16	[8.7,11.7]	2
13	3600	7200	16	[11.4,14.4]	2
14	2400	7800	12	[5.7,8.7]	2
15	6000	4200	19	[5.3,8.3]	2
16	3600	3000	23	[14.9,17.9]	2
17	1800	1200	20	[3.2,6.2]	2
18	3600	600	8	[5.1,8.1]	2
19	1200	2400	19	[6.5,9.5]	2
20	600	3600	2	[14.7,17.7]	2
21	2400	4800	12	[7.7,10.7]	2
22	1800	7200	17	[6.6,9.6]	2
23	5400	7800	9	[11.6,14.6]	2
24	5400	2400	11	[5.2,8.2]	2
25	5400	1200	18	[8.7,11.7]	2
26	6600	600	29	[5.8,8.8]	2
27	7800	4200	3	[14.3,17.3]	2
28	7800	2400	6	[15.6,18.6]	2

3) The driving speed is 30Km/h;
4) The maximum load of delivery staff is 50 Kg;
5) The timeout penalty cost per unit is 2 CNY/min.

As a comparison, GA is used as a baseline to test the effectiveness of IDMCR and AGA-DCR. The parameters of GA and AGA-DCR are shown in Table 5.

For MDMCR, the location of each customer point is classified by the nearest distance method according to Euclidean distance. After the distance to each branch is obtained, the customer point is directly allocated to the nearest branch for delivery, as shown in Fig. 9. As we can see, the dotted line is used to divide the customer points into three parts for three branches, and then the branches arrange delivery tasks respectively. Therefore, each branch arranges the delivery task for the purpose of optimizing the total delivery cost of itself. IDMCR is to directly solve the delivery routing problem of multiple branches in one-stage approach, so there is no need to divide customer points in advance, as shown in Fig. 10.

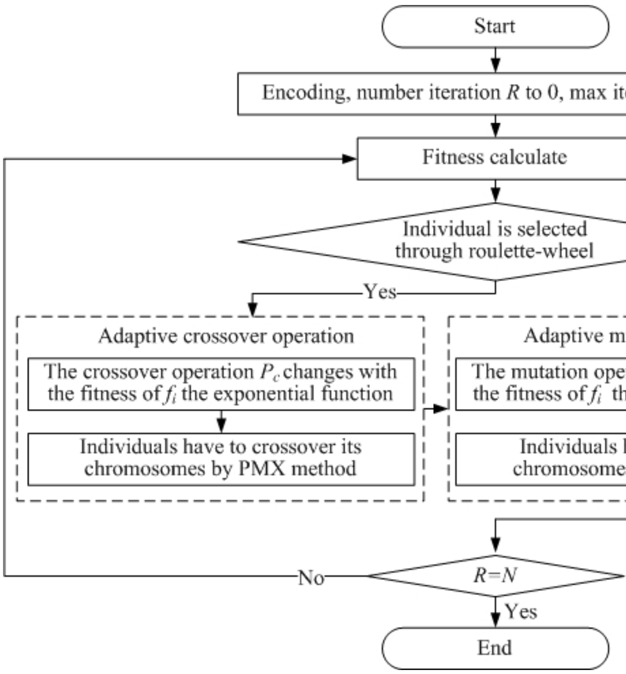


FIGURE 8. Flow chart of AGA-DCR.

TABLE 5. Parameters of algorithms.

Parameters	AGA-DCR	GA
S(the size of population)	100	100
PS	0.9	0.9
Iterations	3000	3000
β1	0.8	-
β2	2	-
α1	0.8	-
α2	2	-
Possibility of Mutation	-	0.8
Possibility of Crossover	-	0.8

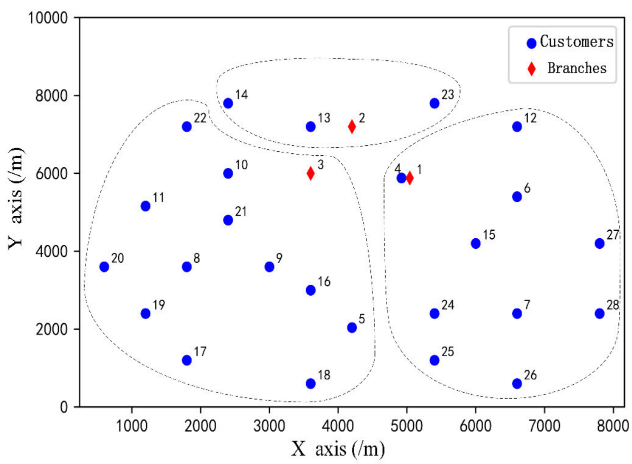


FIGURE 9. Classified customer points and branches for MDMCR.

TABLE 6. The comparison result.

Results	MDMCR with GA	IDMCR with GA	IDMCR with AGA-DCR
Running Time/s	53	45	44
Distance Cost/CNY	117.5	119.6	125
Fixed Cost/CNY	18	18	18
Timeout Penalty Cost/CNY	69.5	30.4	18
Total Delivery Cost/CNY	205	168	161

B. RESULTS

To verify the effectiveness of innovative modes and algorithms, MDMCR with GA, IDMCR with GA and IDMCR with AGA-DCR are tested on the same dataset mentioned above. And the comparison results are shown in Table 6.

For brevity's sake, we describe a mode combining a algorithm as 'mode + algorithm' in the following. According to Table 6 and Fig. 11, IDMCR+GA reduces 56.2% of the timeout penalty cost and 18% of the total delivery cost compared with MDMCR+GA. Compared with IDMCR+GA, IDMCR+AGA-DCR decreases the timeout penalty and the total delivery cost by 40.9% and 4% respectively. IDMCR + AGA-DCR even reduces 74.1% of the timeout penalty cost and 21.5% of the total delivery cost compared with MDMCR + GA.

Although IDMCR increased the distance cost slightly, it saves the timeout penalty and total delivery cost greatly. The optimal scheme, IDMCR combined with AGA-DCR, which lowers the total cost and the number of delivery delays, surely solves the delivery routing problem of chain restaurants.

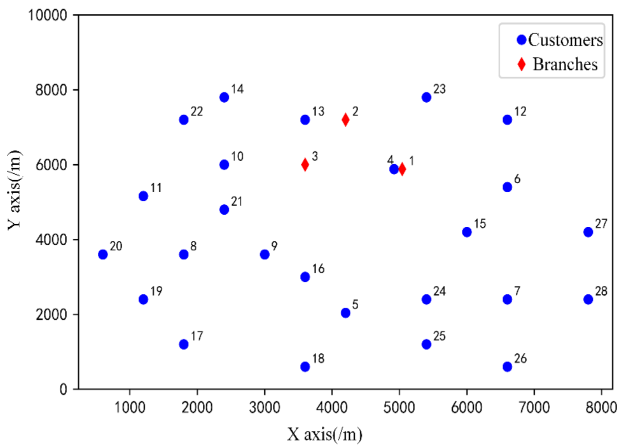


FIGURE 10. Customer points and branches for IDMCR.

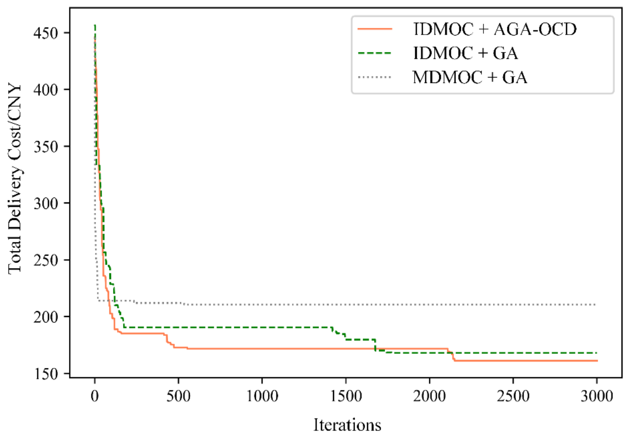


FIGURE 11. Iteration curves of combinations of modes and algorithms.

C. VISUALIZED DELIVERY ROUTES

After calculation, the optimal route plan of the scheme, MDMCR combined with GA, is shown in Table 7. The optimal route planning of the optimized scheme, IDMCR combined with AGA-DCR, is shown in Table 8. In order to provide an intuitive solution for the chain restaurants, two delivery route planning approaches are visualized respectively in Fig. 12 and Fig. 13.

The optimal delivery route of MDMCR with GA is shown in Fig. 12. We can easily see that each branch are arranged the delivery tasks respectively. MDMCR is a kind of single depot vehicle routing problem. Therefore, each branch is arranged the delivery task for the purpose of optimizing the total delivery cost of itself. In this task, 9 delivery staff are assigned with delivery tasks in total, 3 staff in branch 1, 1 staff in branch 2 and 4 staff in branch 3. The specific delivery route information is shown in Table 7, in which "1-12-4-1" refers to a delivery staff of branch 1 and its delivery sequence.

The optimized scheme is IDMCR combined with AGA-DCR. When arranging delivery tasks, each customer point is not limited by distance. The optimized scheme is to solve directly the problem of multiple depot vehicle routing

TABLE 7. Delivery route of MDMCR with GA.

r	K_r	Optimal Delivery Route
1	1	1-12-4-1
1	2	1-15-27-6-1
1	3	1-15-28-26-24-1
1	4	1-7-25-5-1
2	1	2-23-13-14-2
3	1	3-22-10-3
3	2	3-8-11-20-3
3	3	3-19-17-18-3
3	4	3-21-9-16-3

TABLE 8. Delivery route of IDMCR with AGA-DCR.

r	K_r	Optimal Delivery Route
1	1	1-12-6-27-1
1	2	1-24-25-7-1
1	3	1-26-28-1
1	4	1-15-9-1
2	1	2-13-14-23-2
3	1	3-5-18-16-3
3	2	3-8-11-3
3	3	3-22-10-21-4-3
3	4	3-17-19-20-3

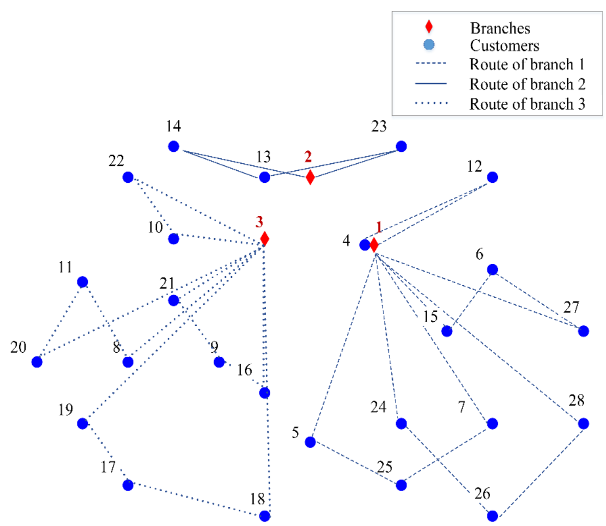


FIGURE 12. Visualized delivery route of MDMCR with GA.

problem in one-stage approach. Therefore, considering the distance and time window of each customer point, the number of delivery delay and the total cost are reduced significantly, although the distance cost is slightly increased. In this task, branch 1,3 and 4 assign 4, 4 and 1 staff respectively. It can be obtained that the improvement of the mode and algorithm can reduce the delivery cost without changing the number of staff.

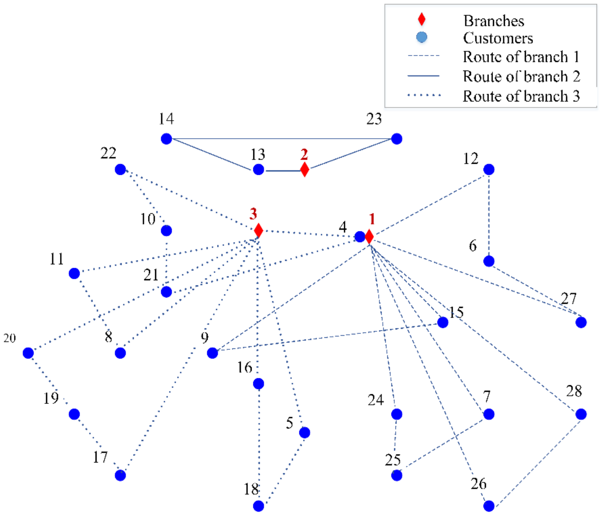


FIGURE 13. Visualized delivery route of IDMCR with AGA-DCR.

Fig. 13 represents the optimal delivery route planning. It's obvious that compared with Fig. 12, it can span the service scope of each branch which significantly improves the delivery delay As the optimal route planning shows, instead of dividing customer points by distance, the time window and distance of each customer point are taken into account to minimize the total delivery cost.

VI. DISCUSSION

In this study, the main problems of chain restaurants are decentralization during the peak meal period, the severe delivery delays and the high total delivery cost. The general idea to solve these problems is to adjust the distributed management mode to the centralized management mode first, and then establish the models considering the constraints of timeout penalty cost, fixed cost and distance cost; Finally the heuristic algorithm is used to solve the delivery routing problem. Instead, our work is to change the two-stage approach into the direct method to solve MDVRPTW. And an optimized genetic algorithm is proposed to improve the performance of GA, MDMCR and IDMCR we established. AGA-DCR is designed according to the characteristics of IDMCR. Comparison results between MDMCR and IDMCR, GA and AGA-DCR, are shown as follows.

GA is used to solve the VRP of MDMCR and IDMCR respectively as an optimizing algorithm to verify the higher effectiveness of IDMCR, which represents that one-stage approach outperforms two-stage approach in solving MDVRPTW.

GA and AGA-DCR are used for IDMCR separately to verify the performance of AGA-DCR, which indicates that AGA-DCR is suitable in this complex situation.

Through these comparisons, it can be concluded that IDMCR with AGA-DCR has the best performance with less delivery delays and lower total delivery cost. Moreover, the optimized delivery route planning is visualized, which provides a feasible scheme for chain restaurants. In addition, this study also provides the following suggestions for the construction of delivery mode of chain restaurants during the peak meal period:

The delivery staff of the nearby branch can be reasonably assigned tasks to lower the timeout penalty. This mode is mathematically formulated as IDMCR, which can be used in the delivery platform and the chain restaurants to sharpen their competitive edge.

Compared with GA, AGA-DCR is more suitable to deal with the problem of delivery route planning, with a shorter running time. During the peak meal period, the proposed IDMCR combines with AGA-DCR achieves better performance. The chain restaurants can decide whether to use this optimized route planning to reduce the total delivery cost and the possibility of delivery delays.

VII. CONCLUSION

This study addresses the delivery routing problem of the chain restaurants with multiple branches. Aiming at the optimization of the delivery routing of chain restaurants, the established mode IDMCR is combined with the improved genetic algorithm AGA-DCR as an optimized scheme for route planning, which has been proved to be able to solve the main problems of VRP during the peak meal period. Through experiments, the timeout delivery and total delivery cost are obviously reduced by the optimized scheme. Also, AGA-DCR jumps out of the local optimal trap effectively with lower total delivery cost. The visualized optimal route planning can provide an intuitive reference for related enterprises.

APPENDIX

VRP	Vehicle Routing Problem
SDVRP	Single Depot Vehicle Routing Problem with Time Windows
MDVRP	Multi-Depots Vehicle Routing Problem
MDVRPTW	Multi-Depot Vehicle Routing Problem with Time Windows
MDMCR	Modern Delivery Mode of Chain Restaurants Genetic Algorithm
IDMCR	Improved Delivery Mode of Chain Restaurants
GA	Genetic Algorithm
AGA	Adaptive Genetic Algorithm
AGA-DCR	Adaptive Genetic Algorithm for Delivery of Chain Restaurants

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Conflicts of Interest: The authors declare no conflict of interest.

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