A Hybrid Genetic Algorithm for Multi-compartment Open Vehicle Routing Problem with Time Window in Fresh Products Distribution

Chunxiao Wang, Hengrui Ma, Defeng Zhu, and Yan-e Hou

Abstract—**This paper introduces an multi-compartment open vehicle routing problem with time window (MCOVRPTW) arising in fresh products distribution, which doesn't require the finished service vehicles return to the distribution center. There are three types of fresh products to be delivered by the multi-compartment vehicles, and the objective aims to find the vehicles scheduling scheme with the lowest cost. For this problem, we established a mathematical model in which the capacity constraint of each compartment and time window constraint must be satisfied. Then, we proposed a hybrid genetic algorithm with some local search-based operators, called GA-LS, to solve it. Each individual in initial population was generated by the nearest neighborhood method to obtain high-quality initial population. When a child population was built, the local search procedure was executed on each individual in the child population to enhance its quality. Finally, we carried out some experiments to evaluate the effectiveness of the proposed algorithm. According to the results, the proposed algorithm can yield better solutions compared with existing approaches. Meanwhile, the proposed algorithm reveals good stability and convergence.**

Index Terms—**multi-compartment vehicles; open vehicle routing problem; time window; fresh products distribution; hybrid genetic algorithm**

I. Introduction

WITH the rapid development and widely application of electronic commerce, online purchasing fresh products has become a trend. It is well know that fresh food is susceptible to spoilage. For the online fresh trade, the fresh food must be transported from fresh food retailers to end customers. It requires the retailers to provide a higher quality of fresh goods service. For fresh distribution enterprises, fresh distribution involves vehicle purchasing, daily operations, and other related operations. The routing planning of service vehicles is the basic part of fresh distribution, which seriously affects the transportation cost. In the case of cost and faced fierce market competition, how to plan the driving routes of vehicles quickly and efficiently has become the focus of fresh distribution enterprises.

Multi-compartment Vehicle Routing Problem (MCVRP) is a new variant of Vehicle Routing Problem (VRP)[1], which has been widely applied in petrol transportation, cold chain and waste collections, etc. Multi-compartment vehicles are used to transport different types of goods together on the same vehicle. For fresh goods, they are divided into room temperature, refrigeration and frozen products according to its demand for temperature. It is very suitable to use the multi-compartment vehicles to delivery fresh goods. To keep the quality of service, the multi-compartment vehicles must arrive at the customer nodes in the pre-defined time windows. The vehicles usually need return to the distribution center when they serve all the customers. But for some fresh enterprises, they dont have the ability to provide logistics distribution, and they often resort to third-party logistics companies. It means that the route of vehicles is open. All things considered, we introduce an multi-compartment open vehicle routing problem with time window (MCOVRPTW) in this paper.

As a variant of VRP, MCVRP is also a combinatorial optimization problem, which is extremely difficult to solve. There are a lot of research results about VRP[2-6], but MCVRP has been paid attention only in recent years[7]. MCOVRPTW adds the time window constraints and open route attribute on the basis of MCVRP, so it is more complex than MCVRP. For MCOVRPTW, we consider capacities constraints of each compartments, time windows constraint and open route attribute, which is a new problem arising in the application field of MCVRP. The main objective of this problem is minimize the total cost including vehicle fixed cost, daily operation cost, refrigeration cost and fresh goods damage cost.

MCVRP was first proposed by Brown and Graves [8] to resolve the dispatch of petroleum problem. From the view of problem definition, MCVRP contains the main elements of typical VRP. The main difference is the use of multi-compartment vehicles, which makes it possible to transport different types of products together. Each distribution node has different types of products to delivery, which usually must be placed in designated compartment of vehicle. In recent years, MCVRP has attracted the attention of researchers. Some VRP-related attributes, such as time window [9,10], heterogeneous vehicle fleets[11] and multi-depot[12],are introduced to MCVRP. The recent review of MCVRP is given in [7,13].

The general MCVRP considers only capacity constraint of each compartment. Reed et al.[14] proposed an ant colony

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system algorithm for MCVRP associated with collection of recycling waste from households to minimize the total travel distance. Abdulkader et al.[15] was based on the work of Reed et al.[14] and proposed a hybridized ant colony algorithm with local search to solver MCVRP considering tour duration limitations. After that, Kaabachi et al.[16] introduced a self-adaptive variable neighborhood search and hybrid artificial bee colony method to solve petrol station replenishment problem. Yahyaoui et al.[17] addressed the same problem and then proposed two methods, variable neighborhood search and genetic algorithm. The related research on this problem also are proposed in [18-19].

Multi-Compartment Vehicle Routing Problem with Time Windows (MCVRPTW) is the variant of general MCVRP by adding time window constraint. Chen et al.[20] introduce a problem in perishable food distribution with time windows whose optimization objective consists of fixed and variable cost as well as fuel consumption cost. The authors present an adaptive large neighborhood search (ALNS) to solve the problem. Chen and Shi[8] discuss MCVRPTW occurring urban last-mile distribution and propose a hybrid particle swarm optimization method. Xu et al.[21] proposed a variable neighborhood descend method to solve refined product distribution problem with multiple optimization objectives. In the research of Rachmavati et al.[22], the authors use genetic algorithm to solve waste collection problems to reduce the wasting collection and transportation costs. In these mentioned above research, the vehicles starts from the depot and return to depot after finishing service. But, with the development of third-party logistics, the vehicles dont have to return to the distribution center after finishing delivering. It makes the travel route of vehicles be open. Therefore, when allowing the routes open, the MCOVRPTW problem can be addressed on the basis of MCVRPTW.

MCOVRPTW can also be considered as a variant of Open Vehicle Routing Problem with Time Window (OVRPTW), which has been widely used in newspaper distribution, express service, school bus service, etc. Compared with the VRP with time windows, there are fewer studies on the OVRPTW [23-27]. Repoussis et al.[23] and reference[24] both solve OVRPTW, the former designed a forward greedy algorithm, and the other implemented a multi-start tabu search algorithm(MS-TSA). Perwira et al.[25] proposed a particle swarm optimization hybrid with path relinking to minimize the total vehicle travel distance of OVRPTW. Brandao[26] introduced an iterated local search algorithms with effective use of ejection chains and elite solutions to solve OVRPTW. In addition, the authors also provided a large amount of OVRPTW examples for the first time. Xia and Fu[27] minimize two objectives of OVRPTW, which consists of the number of vehicles, total traveling distance cost and satisfaction rate related objective, and employ an improved tabu search algorithm to solve it.

From the above description, there have sprung some successful methods for MCVRPTW and OVRPTW, but the MCOVRPTW problem has not been paid attention. These successful experience in MCVRPTW and OVRPTW encourage us to develop effective algorithm for solving MCOVRPTW. Genetic algorithm is a classical population metaheuristic, which has been widely applied in many combinatorial optimization problems[16,22]. Therefore, we try to design a hybrid genetic algorithm that adopt strategies such as the initial population generation method, multi-neighborhood structure embedded in local search procedure to solve the addressed problem in this paper.

The main contributions of this paper are described as follows. First, we analyze the composition of each optimization objective and then build the mathematical model of MCOVRPTW. Second, a hybrid genetic algorithm named GA-LS is proposed to solve the proposed problem, which incorporates three local search operators to improve the quality of population. To get better initial population, a nearest insertion method is adopted to get an initial individual. Finally, several experiments are conducted on benchmark instances to evaluate the effectiveness of the proposed algorithm. Extensive experiments show that the proposed algorithm is very effective and has good stability and convergence.

The rest of this article is organized as follows. Section 2 gives the description of the addressed problem and its mathematical model. The proposed algorithm is introduced in Section 3. The performance evaluation and analysis of the presented approach is given in Section 4. Finally, section 5 makes a conclusion and points out the future research direction.

II. Problem Description and Model

A. Problem Description

The MCOVRPTW problem addressed in this paper is described as follows. There is a distribution center and several customer points in a region. The distribution center, that is depot, has several homogeneous multi-compartment vehicles that are provided by third-party logistics company. Each vehicle starts from depot and visits customers in sequence. After the vehicle finishes service, they dont have to return the depot. There are three types of fresh products to delivery, including room temperature, cold storage and frozen products. The fresh products should be placed in the corresponding compartment in vehicle. Each customer have a certain demand of products, and it also has a time window. Each customer must be visited only once by one vehicle. At any time, the total load of products in each compartment of vehicle cannot exceed the capacity constraints of the compartment. All the total cargo load on the vehicle must be exceed the maximum capacity of the vehicle. The vehicle are required to arrive the customer between the earliest and latest time. The main goal of the problem is to minimize the total cost, which consists of fixed vehicle cost, daily operation cost, refrigeration cost and cargo damage cost.

B. Symbols Definition

Before building the mathematical model of the MCOVRPTW, we first give the definitions of related symbols including sets, parameters and decision variables. They are shown as follows.

Sets

- V: the set of depot and customers, $V = \{0, 1, 2, 3, ..n\}$, where 0 is the depot
- N: the set of customers, $N = \{1, 2, 3, ..n\}$
- K: the set of vehicles, $K = \{1, 2, ..k\}$
- P: the set of types of fresh products, $P = \{1, 2, ..p\}$

Parameters

- F_k: the fixed cost of vehicle k
- d: travel cost from customer i to customer j
- t_{ij}: travel time between two customer i and j
- q_{ip}: demand of customer node i for good p
- Q_p: the capacity of the compartment p
- s_{ik}: arrival time of vehicle k at customer node i
- et_i: the earliest beginning time window of customer i
- lt_i: the latest beginning time window of customer i
- w_i: the service time at customer i
- f_p: refrigeration cost coefficient of product p
- θ_0: initial freshness value of each product
- θ_{ip}: the freshness value of product p at customer node i
- σ_p: decay coefficient of product p
- ε_p: fresh-keeping investment value of fresh product p
- G_p: the damage coefficient of product p

Decision variables

- x_{ijk}: if the vehicle k travels directly from customer i to customer j ,then x_{ijk} =1; otherwise x_{ijk}=0
- y_{ik}: if customer node i is served by vehicle k,y_{ik} =1, otherwise y_{ik} =0

C. Optimization Objective Definition

In this section, we analysis the optimization objective of the problem. The first objective is total fixed cost, which is related to the number of vehicles. We let F_k represent the fixed cost of vehicle k, consisting of purchase or rent cost of vehicles, drivers wage and maintenance fee, etc. Here F_k is set to 20. The fixed cost is defined as:

$$F_1 = \sum_{k=1}^{K}\sum_{j=1}^{N} F_k x_{0jk} \tag{1}$$

The daily operation cost is defined in equation (2), which are the total cost of all the vehicles.

$$F_2 = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} d_{ij}x_{ijk} \tag{2}$$

The third objective is the refrigeration cost. According to the characteristics of fresh product, some fresh product must be kept in cold storage or frozen, resulting in increasing the fuel consumption. We give a refrigeration coefficient to every fresh product, so the total refrigeration cost is calculated by equation (3). For room temperature product, cold storage product and frozen product, their f_p values are set to 0.1, 0.3 and 0.5 respectively.

$$F_3 = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{p=1}^{P} f_p q_{ip} y_{ik} \tag{3}$$

The last objective is cargo damage cost. In the transportation process of fresh product, the loss of water and the impact of other factors will cause damage of product. As mentioned in [21], the freshness value of product p at customer i is defined in equation (4). Each type of fresh product has a damage coefficient G_p, which are set to 1.5, 2.5 and 5.0 for room temperature product, cold storage product and frozen product. So, the total cargo damage cost is calculated by equation (5).

$$\theta_{ip} = \theta_0^{(\sigma_p-(1-e^{-\varepsilon_p}))} \tag{4}$$

$$F_4 = \sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{p=1}^{P} y_{ik}G_p q_{ip}(\theta_0 - \theta_{ip}) \tag{5}$$

In equation (4), the values of σ_p of three types of fresh products are set to 2.0, 2.2 and 2.5 respectively. In the same way, for three types of fresh products, ε_p are separately set to 0.2, 1.8 and 5.0. The initial freshness value of each product 0.98.

Therefore, the objective function of the MCOVRPTW problem is shown in equation (6).

$$F{=}F_1 + F_2 + F_3 + F_4 \tag{6}$$

D. Mathematical Model

Based on the above, the mathematical model of the addressed problem is built as follows.

Minimize F

Subject to:

$$\sum_{k=1}^{K} y_{ik} = 1, \forall i \in N \tag{7}$$

$$\sum_{i=1}^{N} x_{0ik} = 1, \forall i \in N, k \in K \tag{8}$$

$$\sum_{\mathrm{i}=1}^{N} x_{i0k} = 0, \forall i \in N, k \in K \tag{9}$$

$$\sum_{i \in N} y_{ik}q_{ip} \leq Q_p, \forall p \in P, k \in K \tag{10}$$

$$s_{jk}{+}w_i + t_{ij} - s_{jk} \leq (1{-}x_{ijk})M \tag{11}$$

$$\sum_{i\in S}\sum_{\mathrm{j}\in S} x_{kij} \leq |S| - 1, \forall S \subseteq N(S \neq \emptyset), i \neq j, \forall k \in K \tag{12}$$

$$et_i \leq s_{ik} \leq lt_i \tag{13}$$

$$x_{ijk} \in \{0,1\}, \forall i \in N, \forall j \in N, \forall k \in K \tag{14}$$

$$y_{ik} \in \{0,1\}, \forall i \in N, \forall k \in K \tag{15}$$

Equation (6) represents the objective function. Equation (7) indicates that each customer can only be served by the vehicle once. Equations (8) and (9) indicate that all vehicles must start from the depot, but do not have to return to the depot. Equation (10) indicates the capacity constraint of the compartment, that is, the total load in the compartment cannot exceed the maximum capacity of the compartment at any time. Equation (11) represents the continuity of vehicle delivery time, where M is a very large positive number. Equation (12) eliminates the subloop constraints. Equation (13) ensures that the service time of the vehicle must be within the customer's time window. Equations (14) and (15) are decision variables.

III. Solution Approach

A. Outline of GA-LS

Genetic Algorithm (GA) is essentially a kind of evolutionary law that learns from the biological world, and its role is to achieve the survival of the fittest. GA operation includes three basic genetic operators: selection, crossover and mutation. GA-LS introduces the nearest neighbor algorithm and local search algorithm to improve the classical GA and overcomes the shortcomings that GA is easy to fall into the local optimal solution. GA-LS further enhances the local search ability and maintains the strong global search characteristics of GA.

The basic flow of hybrid genetic algorithm (GA-LS) is as follows.

(1) Set population size N, maximum number of iterations T_{max}, iteration variable t=0, the parameters of crossover probability cp and mutation probability mp.

(2) Generate N giant tours by the nearest neighborhood method, and then N chromosomes are obtained.

(3) Calculate fitness value of each individual, and the optimal individual in population S is recorded as S_{best}.

(4) For population S, apply roulette selection method to select individuals. The sequential crossover operator selects two parent chromosomes with a certain probability and carries out gene recombination through the crossover. Mutation operators are exchanged with a certain probability to increase the diversity of chromosome combinations in population. Finally, the child population $ChildS$ was obtained by comparing the fitness values of the parents and the optimized offspring.

(5) Calculate the fitness of each individual in the new population $ChildS$, the best individual is denoted as S_{cbest}. If S_{cbest} is better than S_{best},then $S_{best} = S_{cbest}$.

(6) For each individual in new population $ChildS$, apply local search procedure, and then update the global solution S_{best}.

(7) $t++$; If $t <= T_{max}$, $S = ChildS$, then jump to step (4).

(8) Output the optimal solution S_{best}.

B. Encoding and Decoding

In this paper, the chromosomes are encoded by natural integer numbers. 0 represents the depot, and $1 \sim n$ represents customers. For example, $\{1, 6, 4, 3, 5, 2\}$ is a chromosome, which shows the visiting sequence of the vehicles. When a chromosome is transformed into the solution of the MCOVRPTW problem, the procedure of decoding is described as follows. Considering the problem constraints, the route of each vehicle starts from 0 and ends with the customer. The vehicle starts with the first customer point of a chromosome. If this customer point can be inserted into the route without violating the constraints of the capacity and time window, it is inserted into the route. Otherwise, a new route is constructed to insert the customer point. Repeat this process until all customer points are located in the routes.

C. Generating Initial Population

This paper adopts the nearest neighbor algorithm to construct a great tour including all the customers. The reason is that randomly generation of initial population is usually to be bad and the quality of algorithm cannot be guaranteed. The great tour is also a chromosome. The specific generation process is to first randomly select a customer as the current point and add it to the current chromosome. Then, according to the current node, the nearest customer point is selected to be append behind the current node. Repeat the selection and append process of the nearest customer point related to the current node, until all the customers are inserted into the chromosome. This generation process of a single chromosome is repeated many times to obtain the initial population.

D. Selection

In this paper, we use roulette selection operator to select individual. Roulette selection operator is the most basic and commonly used selection operator in genetic algorithm. Due to the comparison of parental and offspring chromosome fitness values, one-to-one survival competition is used to retain the minimum fitness value and update the parental population. First, all chromosomes are decoded and their fitness values F are calculated. The sum of the fitness values for all chromosomes in the current population is defined in Equation(16). Then, the selection probability $p(i)$ of each chromosome is shown in Equation (17). The cumulative probability $p\_sum(i)$ of each chromosome being selected are calculated in Equation (18). Finally, a random number between 0 and 1 is generated for each chromosome of the population, and each random number is compared with the cumulative probability of each chromosome in turn. If the cumulative probability is greater than that of the i chromosome and less than that of the $i+1$ chromosome, the $i+1$ chromosome is selected to enter the next generation.

$$Fit = \sum_{i=1}^{N} F(i) \tag{16}$$

$$p(i) = F(i)/Fit \tag{17}$$

$$p\_sum(i) = \sum_{i=1}^{N} p(i) \tag{18}$$

E. Crossover

We employ sequential crossover operator (OX) to select two parent chromosomes in the current population with a certain probability. The offspring individuals with higher fitness are generated by the crossover gene recombination. The sequential crossover operator preserves the relative order of the genes of both parents as much as possible, which can help to inherit the chromosome fragments of excellent individuals to their offspring. Meanwhile, sequence crossover operator play an important role in global search, increasing the solution space of search.

As shown in Fig. 1, there are the two parent chromosomes, which are Parent1=$\{6, 2, 4, 3, 5, 1\}$ and Parent2=$\{1, 6, 5, 2, 4, 3\}$. The two customer sites of the chromosome 2 and 4 are randomly selected. The child Offspring1 retains the customer points 2, 4, 3 between positions 2 and 4 of the parent chromosome. The other customer point in parent Parent2 are inserted into Offspring1 in order. If the existing

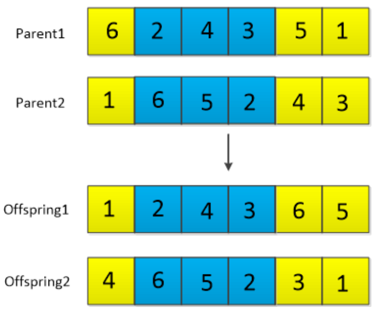


Fig. 1. sequential crossover operator

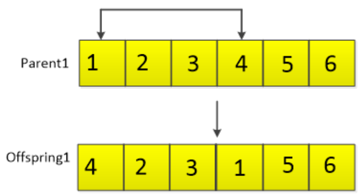


Fig. 2. mutation operator

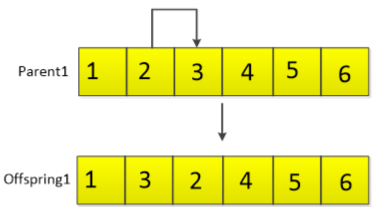


Fig. 3. single point movement

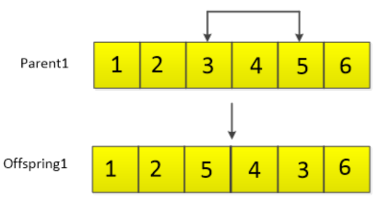


Fig. 4. two-point exchange

customer point is encountered and skip it, resulting in the final offspring Offspring1={1, 2, 4, 3, 6, 5}. Similarly, the final child Offspring2 is {4, 6, 5, 2, 3, 1}.

F. Mutation

Mutation operator is exchanged with a certain probability to increase the diversity of chromosome combinations in population. The specific process is shown in Fig. 2. Assuming a chromosome Parent1 is {1, 2, 3, 4, 5, 6}, two mutation positions 1 and 4 are randomly selected, and then the values 1 and 4 at the two position points are exchanged to obtain a new individual Offspring1={4, 2, 3, 1, 5, 6}.

G. Local search procedure

To improve the local search ability of traditional genetic algorithm, the local search procedure are introduced in GA-LS. The local search procedure use three neighborhood operators to optimize the generated children, including single point move, two points exchange and 2-opt. These three neighborhood operators is executed in sequence. When the

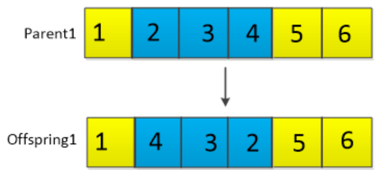


Fig. 5. 2-opt

current neighborhood operator cannot find a better solution than the current solution, the next neighborhood is used, until all the neighborhood operator are all used. The basic description of neighborhood operator is described as follows.

(1)Single point movement. Seen from Fig. 3, customer point 2 is removed from an individual Parent1={1, 2, 3, 4, 5, 6}, and then inserted into another position. A new neighborhood solution {1, 3, 2, 4, 5, 6} is obtained.

(2)Two points exchange. As shown in Fig. 4, the customer points 3 and 5 of Parent1={1, 2, 3, 4, 5, 6} are exchanged, and then a new solution is {1, 2, 5, 4, 3, 6}.

(3)2-opt. 2-opt removes two edges within the route and then adds two more edges, while reversing the path. As shown in Fig. 5, select the edge of positions 1 and 2 and the edge of positions 4 and 5 in Parent1={1, 2, 3, 4, 5, 6}, then break them. The 2, 3, 4 customer points are reversed, and then the edge of positions 1 and 2 and the edge of positions 4 and 5 are added to get a new solution {1, 4, 3, 2, 5, 6}.

IV. Experimental Results and Analysis

A. Experimental setup and parameter settings

This algorithm was coded in PyCharm using python3.7. All experiments were run on personal computers. The machine is configured with Intel(R)core(TM) i5-11400H CPU and 16.0GB RAM. The parameters of hybrid genetic algorithm are set in the following: iteration number T_{max}=500, population size N=50, crossover probability cp=0.95, and mutation probability mp=0.1. Each instance was executed 10 times.

B. Test instances

In order to verify the effectiveness of hybrid genetic algorithm for MCOVRPTW, this paper uses a public data set for experimental analysis. However, due to the lack of internationally recognized examples of MCOVRPTW, Solomon [28] standard examples are adapted. Solomon data set with 50 customers are divided into six sets: C1, C2, R1, R2, RC1, RC2. We select C101∼C104, C201∼C204, R101∼R104, R201∼R204, RC101∼RC104 and RC201∼RC204 as benchmark instances. These instances were adapted by the rule defined in [14]. Because there are only two compartments in the case of adaptation, fresh products are divided into refrigerated and frozen ratio of 2:1 and room temperature and frozen ratio of 3:1.

C. Improvement validation analysis

To evaluate the effective of improved modules in the proposed algorithm, we build three variants of our GA-LS algorithm. GA-LSA as a traditional genetic algorithm, which has neither initial solution generation strategy nor local search algorithm. GA-LSB only uses a local search algorithm and has no initial solution generation strategy. GA-LSC uses the nearest neighbor algorithm(NN) to generate the initial solution and does not use the local search algorithm. Then, we employ four algorithms to sovle MCOVRPTW instances and the results of them are shown in TABLE I. The columns BestAvg, AvgMean, AvgStd and AvgTime represent the average value of best solutions, average solutions, standard deviation and computation time on 24 solomon instances with 50 customers. The column BestNum is the number of best solutions found by the algorithm.

As reported in TABLE I, compared with GA-LSB and GA-LSC, the best solution of the GA-LS algorithm on average are decreased by 11.88% and 0.10% respectively, and the average solution on average are improved by 13.69% and 0.38% respectively. By comparing GA-LSA and GA-LSC algorithms, using the nearest neighbor algorithm to construct the initial solution is better than the random strategy to generate the initial solution. It can seen that local search algorithm only plays the role of searching within the range of the existing solution space when compared GA-LSA and GA-LSB. To sum up, the GA-LS algorithm not only has better solution quality than the GA-LSB and GA-LSC algorithms, but also proves that it has better optimization performance and stability.

D. Results on MCOVRPTW instances

We compare our GA-LS with the existing genetic algorithms, namely GA and GA-SA, proposed by [22] and [29]. TABLE II gives the results of three algorithms on MCOVRPTW, where columns Best, Avg and Std represent the best solution, average solution and standard deviation, respectively.

As shown in TABLE II, GA-LS can find the best solution and average solution,and has good stability. Compared with the GA-SA algorithm, GA-LS has improved the best and average solutions on average by 15.94% and 17.95%, respectively. The GA-SA algorithm is superior to GA, increasing best solutions on average by 4.40%, but decreasing by 0.56 in the mean deviation. GA-LS has better average variance than GA and GA-SA, which is reduced by 6.11 and 6.67. Therefore, the GA-LS algorithm is better than the algorithms GA and GA-SA in solving the MCOVRPTW problem.

E. Results on OVRPTW instances

Further, we evaluate the advantages of GA-LS on OVRPTW instances. GA-LS was compared with the basic genetic algorithm(GA) and the HybridGA algorithm proposed by [30], which adds 2-opt on the basis of GA. First, we use our algorithm to solve OVRPTW instances with 50 customers. It is worth noting that the optimization objective of OVRPTW is the total distance, so the results of the three algorithms are shown in TABLE III.

As shown in TABLE III, we have some findings. Compared with GA algorithm, HybridGA has improved the average value of the best solution by 1.08%, and the average variance has decreased 0.68. Compared with HybridGA, the average value of GA-LS on the best solution and the average solution improved by 15.37% and 19.85% respectively, while the average variance decreased 6.89. Compared with GA and HybridGA, GA-LS not only improves the best solution, but also has better stability of the algorithm. Therefore, the GA-LS algorithm is better than these two algorithm in solving the OVRPTW problem.

Further, we uses GA-LS to solve the OVRPTW problem with 100 customers. The experimental results of GA-LS are compared with those of Repoussis[23] and MS-TS[24] respectively in TABLE IV. Compared with the Repoussis algorithm [23], GA-LS exceeds it on 11 instances and the average value of the best solution is improved by 11.83%. GA-LS is also better than the MS-TS algorithm[24] on 9 cases and the average of the best solution is decreased by 2.61%. Compared with these two algorithms, the average deviation values(column G_1 and G_2) of GA-LS is 7.21% and 0.17%, respectively. Therefore, it is proved that GA-LS algorithm is effective in solving large-scale OVRPTW problem.

F. Stability analysis of the proposed algorithm

In this section, we analysis the stability of the proposed algorithm on different types of instances. Solomon instances are classified into three types: R(random), C(cluster) and RC(random and cluster). We calculated the average standard deviation values on different types of instances. Fig.6 shows the results of the proposed algorithm and its comparison algorithms on MCOVRPTW and OVRPTW respectively.

As shown in Fig. 6, the proposed algorithm has smaller average standard deviation on all instances. For the MCOVRPTW, compared with GA[22] and GA-SA[24], the GA-LS algorithm has the largest differences on RC instances, which are 10.22 and 10.77 respectively. For the R instances, the difference between the GA-LS algorithm and its two comparison algorithms is the smallest. The result in Fig. 6(a) show that GA-LS algorithm is very stability. For the OVRPTW, the GA-LS algorithm still has the smallest standard deviations on C, R and RC instances. Overall, the GA-LS algorithm is very reliable and stable in two problems.

G. Convergence analysis

In this section, we choose C101, C201, R101, R201, RC101 and RC201 as examples to analyze the convergence of the proposed algorithm. Fig. 7 shows the change curve of objective values when the iteration number increases. The convergence rate of GA-LS algorithm is faster in the early 150 generations of six instances, and is relatively gentle in the later period. As the number of iterations increases, the GA-LS algorithm tends to converge after 300 iterations. It shows that the crossover operator plays the role of global search in the early stage, and the local search algorithm plays the role of searching around the optimal solution in the late stage. According to convergence curves in Fig.7, GA-LS algorithm has good stability on MCOVRPTW problem.

V. CONCLUSION

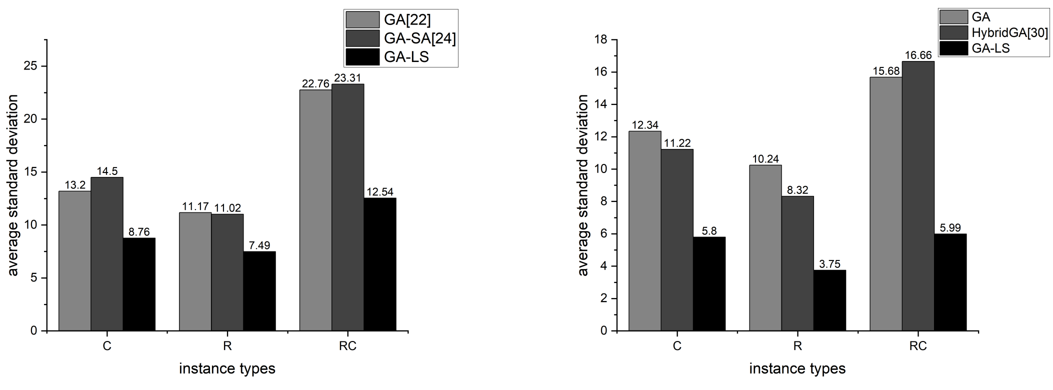
This paper deals with the open multi-compartment vehicle routing problem with time window(MCOVRPTW), which is one of the important applications of multi-compartment vehicle distribution. With the increase of fresh food distribution business in small and medium-sized enterprises, fresh food distribution is often carried out by third-party company. Therefore, this paper designs a hybrid genetic

TABLE I
HYBRID VALIDATION ANALYSIS

Methods	GA	LS	NN	BestAvg	AvgMean	AvgStd	BestNum	AvgTime
GA-LSA	✓			1000.93	1090.09	16.53	0	64.68
GA-LSB	✓	✓		1001.76	1075.13	15.5	0	219.73
GA-LSC	✓		✓	883.68	931.5	9.61	11	62.66
GA-LS	✓	✓	✓	882.76	927.96	9.6	13	210.14

TABLE II
COMPARISON BETWEEN GA-LS AND EXISTING ALGORITHMS ON 50 CUTOMERS

Instance	GA[22]			GA-SA[29]			GA-LS		
	Best	Avg	Std	Best	Avg	Std	Best	Avg	Std
C101	967.21	1032.92	13.75	949.84	1002.8	10.19	732.65	768.82	11.01
C102	919.17	993.07	12.89	891.55	933.23	13.85	723.55	751.24	7.77
C103	891.24	930.42	10.19	830.00	903.6	11.45	688.01	720.18	7.50
C104	786.58	829.74	8.09	739.85	826.02	15.47	609.18	634.75	4.66
C201	1048.19	1128.89	12.96	958.16	1047.56	19.42	772.46	836.10	13.19
C202	958.61	1029.97	15.67	880.31	956.56	16.5	740.83	805.82	9.26
C203	937.92	991.44	14.20	843.54	943.01	21.27	691.99	731.48	8.16
C204	776.07	920.32	17.87	814.29	859.65	7.82	647.7	681.05	8.55
R101	1365.17	1395.68	8.71	1298.45	1355.89	12.92	1273.75	1316.87	9.55
R102	1268.88	1323.71	13.21	1240.08	1283.18	10.57	1124.65	1180.71	11.44
R103	1186.61	1229.94	10.19	1121.65	1192.22	9.83	1050.59	1085.97	7.85
R104	1071.46	1161.58	17.33	1072.85	1113.25	9.01	913.82	936.70	4.89
R201	1195.98	1240.77	8.47	1154.37	1208.40	10.58	1081.46	1117.43	7.19
R202	1112.09	1170.3	9.11	1045.85	1120.74	13.77	960.47	1011.22	6.81
R203	1065.04	1127.62	10.57	1023.41	1071.06	8.5	875.38	900.75	5.07
R204	953.04	1016.56	11.79	937.82	1013.58	12.96	754.78	786.86	7.1
RC101	1421.44	1514.13	18.44	1342.27	1420.90	16.04	1168.87	1254.71	19.55
RC102	1303.67	1411.28	16.56	1255.08	1369.40	24.68	1080.76	1144.97	15.85
RC103	1281.81	1368.96	17.61	1157.95	1293.27	25.71	1000.89	1048.46	9.2
RC104	1179.45	1252.12	26.97	1157.04	1241	17.93	803.99	826.72	5.21
RC201	1313.49	1396.99	23.97	1260.33	1336.25	18.38	1031.35	1095.69	13.66
RC202	1265.55	1355.73	18.79	1186.11	1291.73	22.28	884.28	981.26	16.46
RC203	1110.85	1262.49	27.64	1060.75	1217.92	25.94	863.38	915.32	13.47
RC204	983.98	1154.44	32.09	981.17	1142.77	35.5	711.36	737.9	6.94
Average	1098.48	1176.63	15.71	1050.11	1131.00	16.27	882.76	927.96	9.60



(a) MCOVRPTW (b) OVRPTW

Fig. 6. Average standard deviation of the proposed algorithm and its comparison algorithms on different types of instances

algorithm(GA-LS) to solve the addressed problem in fresh products distribution, which combined local search procedure and improved initial population generation strategy. Compared with the existing algorithms, the GA-LS algorithm is effective when solve the MCOVRPTW and traditional open route vehicle routing problem. Experimental results show that the hybrid genetic algorithm obtains that the initial solution of the nearest neighbor algorithm is better than the random policy. Meanwhile, the local search procedure used in GA-LS can enhance the local search capability of the hybrid genetic algorithm. Moreover, the convergence curves of the proposed algorithm shows its good convergence.

TABLE III
RESULTS OF ALGORITHMS ON OVRPTW PROBLEM WITH 50 CUSTOMERS

Instance	GA			HybridGA[30]			GA-LS		
	Best	Avg	Std	Best	Avg	Std	Best	Avg	Std
C101	413.86	454.91	8.11	428.87	463.05	8.74	302.23	328.09	5.97
C102	381.86	446.76	11.04	372.34	427.04	11.15	294.47	348.77	11.05
C103	392.72	455.93	12.73	393.91	444.18	10.15	290.28	313.71	5.04
C104	340.38	432.30	13.83	363.15	423.41	9.78	265.63	267.18	0.42
C201	497.14	562.01	11.25	467.59	544.96	12.22	422.61	463.56	8.61
C202	443.70	533.48	13.05	461.37	542.61	12.45	413.51	440.25	6.29
C203	490.49	544.57	13.81	485.03	537.53	14.83	392.71	409.75	4.64
C204	450.32	520.64	14.89	452.47	495.39	10.47	362.19	398.35	4.39
R101	739.62	766.78	7.49	743.37	771.50	5.89	715.13	750.83	5.51
R102	698.49	762.03	9.18	715.16	759.18	7.16	688.45	708.64	3.21
R103	680.78	739.22	11.65	710.58	750.67	7.45	644.17	664.89	3.94
R104	660.09	739.11	13.67	668.25	715.43	9.84	583.90	593.39	2.11
R201	695.14	725.16	6.84	690.19	729.24	6.90	662.06	676.21	2.73
R202	664.00	723.82	12.06	690.46	717.81	7.59	596.18	624.60	4.58
R203	662.23	707.90	6.68	662.05	705.72	8.00	555.46	575.87	4.34
R204	637.46	695.92	14.34	579.90	655.87	13.73	513.87	532.94	3.56
RC101	723.18	780.33	11.56	745.72	800.20	10.22	613.51	655.89	6.58
RC102	706.99	768.11	14.08	665.90	737.51	24.06	621.51	651.16	7.38
RC103	645.96	711.32	13.11	676.75	722.65	12.17	542.41	568.41	6.31
RC104	574.04	692.31	21.69	546.24	664.93	21.49	371.46	380.70	3.27
RC201	719.81	752.69	10.43	743.82	790.82	11.00	543.14	600.19	10.51
RC202	650.81	762.11	18.39	658.48	718.30	12.18	505.61	534.08	5.44
RC203	684.98	744.98	12.59	587.49	688.54	18.69	463.08	488.29	5.88
RC204	609.09	703.22	23.60	501.56	592.50	23.47	355.34	366.92	2.51
average	590.13	655.23	12.75	583.78	641.63	12.07	494.07	514.28	5.18

TABLE IV
RESULTS OF ALGORITHMS ON OVRPTW PROBLEM WITH 100 CUSTOMERS

Instance	Repoussis[23]	MS-TS[24]	GA-LS	$G_1(\%)$	$G_2(\%)$
C101	709.71	698.35	807.86	-13.83	-15.68
C102	1036.98	953.62	775.43	25.22	18.69
C103	1146.89	1004.57	736.40	35.79	26.7
C104	907.08	871.72	622.30	31.40	28.61
C105	695.08	695.08	762.01	-9.63	-9.63
C106	871.81	728.54	742.5	14.83	-1.92
C107	679.76	705.32	761.81	-12.07	-8.01
C108	843.74	735.86	709.2	15.95	3.62
C109	745.95	730.65	711.57	4.61	2.61
C201	670.63	664.21	999.83	-49.09	-50.53
C202	971.00	849.92	812.04	16.37	4.46
C203	1281.73	1098.57	771.07	39.84	29.81
C204	1245.54	768.25	732.86	41.16	4.61
C205	694.44	697.37	804.03	-15.78	-15.29
C206	796.02	723.41	767.14	3.63	-6.04
C207	725.29	715.37	710.31	2.07	0.71
C208	691.40	678.67	745.78	-7.87	-9.89
average	865.47	783.50	763.07	7.21	0.17

In the future, we will explore other heuristic algorithms for multi-compartment open vehicle routing problem with time window. In addition, new research topics will be considered on its variants, such as random demand, fuzzy time windows and other problem attributes.

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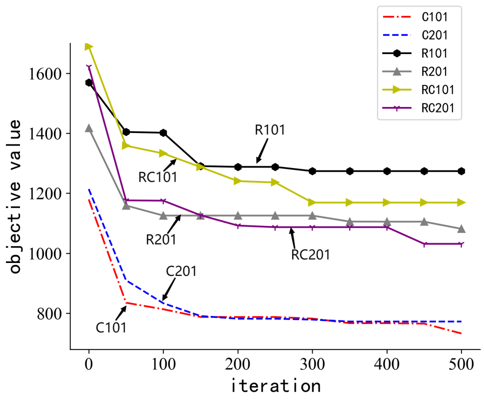

Fig. 7. Convergence curves of different instances

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