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RESEARCH ARTICLE

Loading Method and Routing Optimizations of Fresh Products on Multi-Temperature Joint Distribution With Limited Flexible-Size Compartments

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ABSTRACT The value of fresh agricultural products decreases over time. For customers, timely delivery of products is essential and both freshness and quality are their top priorities. In this paper, a multi-temperature joint distribution problem for fresh agricultural products is studied under a setting where each compartment has a flexible range with defined upper and lower bounds. To characterize the relationship between different loading methods and routing, two realistic optimization models are constructed that can be distinguished into loading-related and routing-related models, simultaneously considering time window and split distribution. Carriers can plan the distribution based on current vehicle availability and estimated cost. To solve the optimization problem, an improved simulated annealing algorithm is designed that reduces the distribution cost and enhances the loading capacity. Numerical experiments are presented to show the effectiveness of the proposed algorithm. The results indicate that different loading and distribution strategies significantly influence the distribution efficiency.

INDEX TERMS Multi-temperature joint distribution, flexible compartments size, defined upper bound and lower bound, time windows, loading method and routing optimizations.

I. INTRODUCTION

The pursuit of healthy and convenient diets by the citizens of developed economies has boosted the demand for various fresh food products [1]. However, fresh agricultural products only remain fit for consumption for a certain period of time after which, their value decreases. For customers, timely production and delivery of these products are therefore essential [2]. Moreover, the freshness and quality of fresh agricultural products are their key priorities [3]. Unlike other foods, the supply chain of fresh agricultural foods is subject to more stringent specifications, where optimal temperature control is necessary to maintain the original value and quality of products [4]. Although cold-chain logistics can essentially guarantee food safety and quality, it is restricted to expensive facilities and equipment [5]. The current trend in fresh agricultural food delivery is moving toward small lot size, high frequency, and multi-temperature delivery, which imposes a significant transportation cost to meet the requirements of timely delivery. Hübner and Ostermeier [6] indicated that specific temperature control during transportation needs to adhere to legislative regulations; they also enumerated the mandated temperatures for different categories of food products in Europe. As different types of food have their own environmental control requirements, traditional refrigerated distribution management with a fixed environmental condition is insufficient [7]. Kuo and Chen [8] developed an advanced multi-temperature joint distribution (MTJD) system to provide precise temperature control, using replaceable cold accumulation or insulation boxes for the food cold chain.

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Doing so can significantly reduce the logistics costs and attain customer satisfaction. Chen and Hsu [9] found that compared to the traditional multi-vehicle distribution system, the MTJD system generates less total emissions.

The problems associated with the MTJD system have been widely discussed in the literature. Topics include the construction of a logistics system [8], the planning of facilities [4], shipment consolidation and the delivery cycle [10], [11], and multi-compartment vehicle routing [6], [12], [13]. The MTJD problem is a variant of the classic multi-compartment vehicle routing problem (MCVRP) in that the temperature within every compartment is specified. In the MTJD problem, a vehicle is divided into two or three compartments by space separation technology such as insulation boards. The temperature within every compartment is specified to keep refrigerated products, frozen products, and ambient-temperature products fresh. This paper focuses on mechanical refrigerated vehicles, which are most widely used in China. These vehicles use refrigerated plates to separate different carriages and have side doors, the positions of which can be customized.

This paper makes the following contributions to the literature:

First, two MTJD models (with or without considering the delivery time requirements for fresh agricultural products) are formulated to characterize the relationship between different loading methods and corresponding total costs. The models also consider a flexible range, mixed time windows, and order splitting by temperature. These additions make the model more useful for carriers, who can effectively manage the allocation of their vehicles while balancing the estimated transportation cost and fulfilling customer demands. Notably, this model can help in a situation where the vehicle fleet capacity is limited. Second, a model is built based on the assumption that each compartment has a flexible temperature range with specified upper and lower bounds. This assumption is made specifically for the most popular one-driving-two mechanical refrigerated truck type. These trucks contain three compartments fitted with refrigerated plates and two side doors to help people get in or out. This paper is the first to consider the attributes of mechanical vehicles in the MTJD problem, increasing its alignment with reality. Third, an improved simulated annealing algorithm is designed to solve the two-stage model and numerical experiments are presented to illustrate the performance of the algorithm. When compared to the model that does not consider a flexible range with a specified upper bound and lower bound, the developed model significantly reduces total transportation cost.

The remainder of this paper is organized as follows: Section II reviews the relevant literature and provides further insights into the research pursued in this work. Section III describes the MCVRP of interest and formulates a two-stage model. Section IV proposes an improved simulated annealing algorithm for solving the problem. Section V presents numerical experiments and the corresponding results. Finally, Section VI summarizes the paper and presents conclusions.

II. LITERATURE REVIEW

MCVRPs have been coined by Brown and Graves [14]. According to further research, these problems can be divided into three streams: MCVRPs with fixed compartment size, MCVRPs with flexible compartment size, and MCVRPs with time windows. The following presents an overview of these three streams.

Research on the MCVRP with fixed compartment size has been reported in a series of papers, including many applications such as fuel delivery [15], bulk shipping [16], distribution of livestock feed [17], [18], as well as recycling and waste management [19], [20]. Cornillier et al. [15] applied MCVRP to solve the multi-period petrol station replenishment problem using an iterative heuristic algorithm. Caramia and Guerriero [16] discussed the multi-compartment distribution problem of milk collection with a heterogeneous fleet, which considered pure trucks and trailers to have heterogeneous capacities. Fallahi et al. [17] developed a memetic algorithm and a tabu search method to solve different types of feed cross-contamination problems. Kandiller et al. [18] studied the daily solution of livestock feed distribution with incompatible products and solved the developed model with a commercial solver. Kiilerich and Wøhlk [19] presented the no-split, commodity-split, and multi-day commodity-split versions of MCVRP to model waste collection problems. Muyldermans and Pang [21] proposed a local algorithm with which they verified the effectiveness of co-distribution and proved that co-collection is better than separate collection. Based on the research of Muyldermans and Pang [21], Silvestrin and Ritt [21] proposed that demands for different product types can be attended in multiple visits without the overhead of representing each demand separately; they presented an iterated tabu search algorithm. Zbib and Laporte [22] also considered MCVRP with commodity split and solved it with a three-phase algorithm. Christiansen et al. [23] developed a genetic algorithm to solve an inventory routing problem in the cement industry where the ship fleet capacity is limited. Moreover, the MCVRP has been discussed in the multi-depot, Internet of Things, and stochastic demands context. For example, Alinaghian and Shokouhi [24] focused on MCVRP in the multi-depot context and solved it with an adaptive large neighborhood search algorithm. Tsang et al. [25] proposed a multi-temperature delivery planning system based on the Internet of Things and developed a two-phase multi-objective genetic algorithm optimizer. Mendoza et al. [26] discussed MCVRP with stochastic demands and proposed a memetic algorithm.

In contrast, MCVRP with flexible compartment size has been studied far less. It can be defined as a MCVRP with discretely flexible compartment sizes and a MCVRP with continuously flexible compartment sizes based on whether the compartment size can be selected as desired. Earlier research on flexible compartments size from Chajakis and Guignard [27] discussed two variants of MCVRP, where a movable bulkhead separates the temperature zones in the second variant. Henke et al. [28], [29] presented a variable neighborhood algorithm and a branch-and-cut algorithm to solve the MCVRP with discretely flexible compartment sizes and the MCVRP with continuously flexible compartment sizes of glass waste recycling. Hübner and Ostermeier [6] studied the MCVRP with continuously flexible compartment sizes in the context of grocery distribution, focusing on the influence of loading and unloading costs.

MCVRP with time windows mainly focuses on two categories: hard time windows and soft time windows. Melechovský [30] discussed the MCVRP with a limited number of vehicles and hard time windows and proposed a variable neighborhood search algorithm to solve it. Kabcome and Mouktonglang [31] presented three mathematical models with multiple trips, hard time windows, and soft time windows for MCVRP and used the software package AIMMS to solve this MCVRP. Chen et al. [32] presented a MCVRP with a higher number of customers and hard time windows in the context of last-mile delivery of urban distribution. They developed particle swarm optimization and hybrid particle swarm optimization with simulated annealing to solve the problem.

So far, research on the order split of MCVRP mainly assessed whether the order is split completely or not at all (no-split). Research on MCVRP with flexible compartment size rarely considered the issue of order split by temperature and by mixed time windows. When studying the MTJD problem with one-driving-two mechanical refrigerated trucks for perishable products, it must be considered that each compartment has a flexible temperature range. Both upper bound and lower bound are defined based on real life rather than based on discretely flexible compartment sizes or continuously flexible compartment sizes. Every order can be split by its temperature and the sub-order of every customer belonging to the same temperature cannot be split. This paper is the first to formulate an MTJD model that considers a limited flexible compartment size range, a mixed time window, and a partial order-split. This model is significantly distinct from the literature.

III. PROBLEM DESCRIPTION AND FORMULATION

The MCVRP with a flexible range for compartment sizes is defined on a complete undirected network with a node-set $N_0 = \{0, 1 \cdots n\}$ consisting of one depot (node 0) and a set N of n customers. Each arc (i, j) has a cost $c_{ij} = c_{ij}$ and the cost parameters are guaranteed to satisfy triangle inequality. At the depot, there are food cold stores of three products including refrigerated products, frozen products, and ambient-temperature products. These must be delivered by a fleet $K = \{1, 2 \cdots k\}$ of identical vehicles, each of which has three flexible compartments. Each compartment of a vehicle is dedicated to a product with known capacity in a specified range $\left[\underline{r_{kp}}\overline{Q_k}, \overline{r_{kp}}\overline{Q_k}\right]$. Each customer j has a known request D_j^p for product p, which can be null for a product not ordered by the customer.

A. PROBLEM ASSUMPTIONS

The problem addressed in this paper is based on the following assumptions:

(1) Demands of all customers must be fully met.

(2) Each vehicle starts its route from the depot and, in the end, returns to the depot.

(3) A customer can be served by multiple vehicles.

B. SETS, PARAMETERS, AND VARIABLES

This section defines the sets, indices, parameters, and variables used in the proposed formulation.

C. MODEL FORMULATION FOR BOTH MTJD PROBLEMS

1) MODEL FORMULATION FOR MTJD PROBLEM WITHOUT CONSIDERING DELIVERY TIME

The decision-making objective of this model is to estimate the number of vehicles required to complete all orders without considering the delivery time. When each refrigerated vehicle can be divided into three compartments with freezing-plates, the proportions of the three compartments in the vehicles are arranged to load all orders with the least number of vehicles. When fewer vehicles are used, the total loading rate is improved. The model referred to as Model 1 can be formulated as follows:

$$Min \sum_{k\in K} \mu_k \tag{1}$$

$$\sum_{k\in K} \mu_k \le |K| \tag{2}$$

$$\sum_{k\in K} q_{jk}^p \ge \overline{D_j^p}, \forall j \in N, p \in P \tag{3}$$

$$\sum_{j\in N}\sum_{p\in P} q_{jk}^p \le \overline{Q_k}\mu_k, \forall k \in K \tag{4}$$

$$\sum_{j\in N} q_{jk}^p \le r_{kp}\overline{Q_k}\mu_k, \quad \forall k \in K\ p \in P \tag{5}$$

$$\sum_{p\in P} r_{kp} = 1, \quad \forall k \in K \tag{6}$$

$$\mu_k \in \{0, 1\}, \quad \forall k \in K \tag{7}$$

$$q_{jk}^p \ge 0, \quad \forall j \in N,\ k \in K,\ p \in P \tag{8}$$

$$r_{kp} \in \left[\underline{r_{kp}}, \overline{r_{kp}}\right], \quad \forall k \in K,\ p \in P \tag{9}$$

The Objective Function (1) represents the minimization of the total number of vehicles. Constraints (2) prevent the numbers of all vehicle violations, and the logistics carrier can set any value based on available vehicles as long as the demand of all customers can be met. Constraints (3) ensure that the demand of every customer for each product is fully met. Constraints (4) and (5) prevent violation of total vehicle capacity and the compartment capacity in each vehicle, respectively. Constraints (6) represent that the sum of the proportions of three compartments in each vehicle is equal to 1. Constraints (7) and (8) specify the binary or nonnegative nature of variables. Constraints (9) represent the

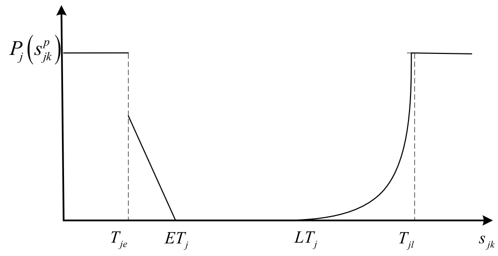

FIGURE 1. **Penalty cost of mixed time windows.**

flexible temperature ranges for the three compartments in each vehicle.

2) MODEL FORMULATION FOR THE MTJD PROBLEM WITH DELIVERY TIME REQUIREMENT

In this model, the delivery time window required by customers is incorporated into the model formulation. The allocation of demands to vehicles in Stage 1 inherently determines the assignment of locations to vehicles in Stage 2. To prevent the delivery route from exceeding the required time window, a penalty is imposed on total distribution costs for orders that do not arrive on time. The value of fresh agricultural products decreases highly over time, and is sensitive to the temperature of storage and distribution. If the vehicle reached the customer too soon, corresponding waiting cost may be generated because of unsuitable storage conditions; in contrast, if the customer is reached too late, high delay costs will be generated. Customers have a certain tolerance for times outside of the time window. Therefore, mixed time windows are used to measure the penalty cost, i.e., to allow vehicles to reach the customer early or late within a certain range but to pay a certain penalty cost. If the time is exceeded, customers will reject the order. The penalty cost of late delivery for vehicle k servicing customer j can be expressed by Figure 1 and Formula (10).

$$P_j\left(s_{jk}\right)=\begin{cases}\alpha \sum\limits_{p\in P}\overline{q^p_{jk}}\left(ET_j-s_{jk}\right), T_{je}<s_{jk}<ET_j\\ 0, ET_j\le s_{jk}\le LT_j\\ \beta \sum\limits_{p\in P}\overline{q^p_{jk}}\left(s_{jk}-LT_j\right), LT_j<s_{jk}<T_{jl}\\ \sum\limits_{p\in P}\overline{q^p_{jk}}, T_{je}>s_{jk}, s_{jk}>LT_j\end{cases} \tag{10}$$

The distribution routine that minimizes the total distribution cost needs to be determined next. The model referred to as Model 2 is formulated as follows:

$$Min \sum_{j\in N}\sum_{k\in K}\bar{f}_k x_{0jk}+\sum_{i\in N_0}\sum_{j\in N}\sum_{k\in K}c_{ij}x_{ijk}+\sum_{k\in K}\sum_{j\in N}P_j\left(s_{jk}\right) \tag{11}$$

Subject to:

$$\sum_{j\in N}x_{0jk}=\sum_{j\in N}x_{j0k}, \forall k\in K \tag{12}$$

$$\sum_{i\in N_0}x_{ijk}=\sum_{i\in N_0}x_{jik}, \quad \forall j\in N,\ k\in K \tag{13}$$

$$x_{ijk}+x_{jIk}\le 1, \quad \forall i\in N_0,\ j\in N, k\in K \tag{14}$$

$$\sum_{i\in N_0}x_{ijk}\ge 1, \forall k\in K, j\in\left\{j\left|\overline{q^p_{jk}}>0, \forall p\in P\right.\right\} \tag{15}$$

$$s_{jk}=s_{(j-1)k}+\overline{t^{service}_{(j-1)k}}+t_{(j-1)k}, \tag{16}$$

$$\forall k\in K, j\in\left\{j\left|\overline{q^p_{jk}}>0, \quad \forall p\in P\right.\right\} \tag{17}$$

$$x_{ijk}\in\{0,1\}, \quad \forall i\in N_0,\ j\in N, k\in K \tag{18}$$

The Objective Function (11) represents the total cost to be minimized, including the fixed cost, the total transportation cost, and the penalty cost. Constraints (12) ensure that each vehicle starts its tour from the depot and also returns to the depot after delivery. Constraints (13) ensure the continuity of each route: if a vehicle enters node j, it must also leave it. Constraints (14) ensure that sub tours are eliminated. Constraints (15) represent that customer j must be visited k by a vehicle if this vehicle brings any product to this customer. Constraints (16) track the delivery time of vehicle k for customer j. Constraints (18) specify the binary nature of variables.

Further, without considering the time window, the solution of Model 1 could be routes that maximize the loading rate but result in late delivery. To solve Model 2, the process starts with an initial feasible solution and then gradually improves the solution by swapping the assignment of locations to vehicles while ensuring that constraints are satisfied. The solution set of Model 1 can be the initial feasible solution set for Model 2.

IV. DESIGN OF SOLUTION ALGORITHM

The MCVRP for mechanical refrigerated trucks with flexible compartment sizes is an NP-hard problem. To solve the problem, an improved simulated annealing (SA) algorithm is proposed in this section. The procedure starts with a genetic algorithm (GA) to identify multiple distribution routes that meet the maximum vehicle loading rate. This constitutes the initial solution set for Model 1. The SA algorithm has higher search efficiency than the GA algorithm and can accept decomposition with a certain probability to avoid falling into local optimization. To expand the search scope and avoid the excessive limitation of the initial solution obtained by Model 1, a neighborhood conversion mechanism and a guiding mechanism are introduced. These are introduced in addition to the basic framework of the SA algorithm to solve Model 2 and re-optimize the solution of Model 1. This design is conducive to balancing efficiency, concentration, and diversity of the search while avoiding getting stuck in local optimization.

A. THE GENERATION OF INITIAL SOLUTIONS CONSTRUCTION BASED ON GA

To improve both performance and efficiency, a clustering algorithm based on GA is used to cluster customer orders and obtain the initial solution set for Model 1. The initial number of clusters C is described in Formula (19), i.e., the lower bound for the number of vehicles required for the distribution of demand.

$$C = max\left(\left\lceil \sum_{j\in N} D_j^p \Big/ \overline{Q_k r_{kp}} \right\rceil\right), \quad \forall p \in P \tag{19}$$

The objective function of the clustering algorithm is as follows:

$$Min \sum_{c=1}^{C} \sum_{j\in Z_c/\{o_c\}} D\left(j, o_c\right) \tag{20}$$

where C is the number of clusters; for $c \in \{1, 2 \cdots C\}$, o_c is the cluster center of cluster Z_c; $D(j, o_c)$ represents the Euclidean distance of order j and the clustering center o_c of cluster Z_c. Based on clustering results, a feasible solution for Model 1 and Constraints (3)–(7) that satisfy the minimum number of vehicles can be constructed.

The clustering procedure is detailed as follows:

Step 1: Cluster order based on transportation distance. All orders are divided into C clusters using GA.

Step 2: Construct initial paths within each cluster. For any $c \in \{1, 2 \cdots C\}$, the order with the smallest distance to the depot in Cluster Z_c is selected as the first order to be visited in path r. The remaining orders that satisfy Constraints (3)–(7) are inserted into path r by the nearest-neighbor method. If no order remains unassigned, jump to *Step 5*.

Step 3: Construct a path that connects different clusters. For orders that remain unassigned and satisfy Constraints (3)–(7), orders are inserted into the path that belong to other clusters by the nearest-neighbor method. Constraints and insertion methods are the same as above. If no order remains unassigned, directly jump to *Step 5*.

Step 4: Increase new paths. For any $c \in \{1, 2 \cdots C\}$, if remaining orders exist that are not assigned to Cluster Z_c, a new path C: $=$ C $+$ 1 is constructed. Unassigned orders are assigned according to the rules described in *Step 2*. Repeat *Step 4* until all orders are assigned.

Step 5: The route set that uses the minimum number of vehicles has been found.

B. OVERVIEW OF THE SIMULATED ANNEALING ALGORITHM

Compared to other MTJD models, in this paper, a multi-product and multi-compartment model with lower bound and upper bound is considered. The number of locations serviced, the positions of these locations, the loading method, and the routes selected all determine the total cost. The problem this paper focuses on is the MTJD problem that allows the condition of each customer to be served by multiple vehicles. The operation between multi-routes involves the conversion of different locations and the shift, swap, and crossover of different items of orders. It also involves the adjustment of items across different vehicles and compartments. Therefore, this paper proposes an improved simulated annealing algorithm with 10 suitable neighborhood structures.

The general SA framework can be described as follows: Given an initial feasible solution x_0, initial temperature T_0 and termination temperature T_{end}, SA starts from x_0, randomly selects neighbor shaking, and calculates the objective function increment. If this increment is below zero, the solution is updated. Otherwise, the solution is accepted with the probability of $P(increment, T)$ and the temperature is lowered to T. The above-described process is repeated until the maximum number of iterations or the termination temperature T_{end} is reached. The designed improved SA constructs 10 neighborhood structures (see Table 2), starting from the two aspects of orders and compartments, and combines it with the neighborhood structures proposed by Henke et al. [28]. Unlike Henke et al. who considered that orders can be split arbitrarily, this paper presents the case that orders are split according to the temperature layer. That is, orders in the same temperature layer cannot be split, a specific example is shown in Figure 2. This improved SA algorithm with various neighbors is called VNSA, and the pseudo-code is shown in Figure 3. The neighborhood structures use three types of operations: shift, swap, and split, following the classical split delivery vehicle routing problem. They can be split into supply-vehicle-assignments and location-vehicle-assignments, respectively.

TABLE 1. All sets, parameters, and variables.

Sets	N	Nodes, denoted by indices *i and j*
	N_0	Set of all nodes and one depot
	K	Fleet vehicle set, denoted by index *k*
	P	Product set, denoted by index *p, p = 1, 2, 3*
Parameters	$\overline{D_j^p}$	Demand for node *j* for product *p*
	c_{ij}	Distance between nodes *i* and *j*
	s_{jk}	Time when vehicle *k* arrives at custom *j*
	$\alpha, \ \beta$	Earlier and later penalty coefficient
	$\left[ET_j, LT_j\right]$	Optimal time window of satisfaction
	$\left[T_{je}, T_{jl}\right]$	Service time window
	$P_j\left(s_{jk}^p\right)$	Penalty cost of time window when vehicle *k* services customer *j*
	$\bar{v}$	Average speed when all vehicles travel from depot to customers
	$\overline{Q_k}, \overline{f_k}$	Capacity and fixed cost of vehicle *k*
	$\left[\underline{r_{kp}}, \overline{r_{kp}}\right]$	Flexible range of each compartment for vehicle *k*
Variables	x_{ijk}	1, if vehicle *k* travels from customer *i* to customer *j*, otherwise 0
	μ_k	1, if vehicle *k* is used, otherwise 0
	q_{jk}^p	Delivery quantity of customer *j* with product *p* by vehicle *k*
	r_{kp}	Ratio of each compartment for each vehicle *k*

V. NUMERICAL EXPERIMENTS

For the numerical examples, this paper generates a random extraction of the features of certain customers from Solomon's data sets. These include locations, demand times, time-window constraints, and items. There is no suitable test case for fresh products with different temperatures in

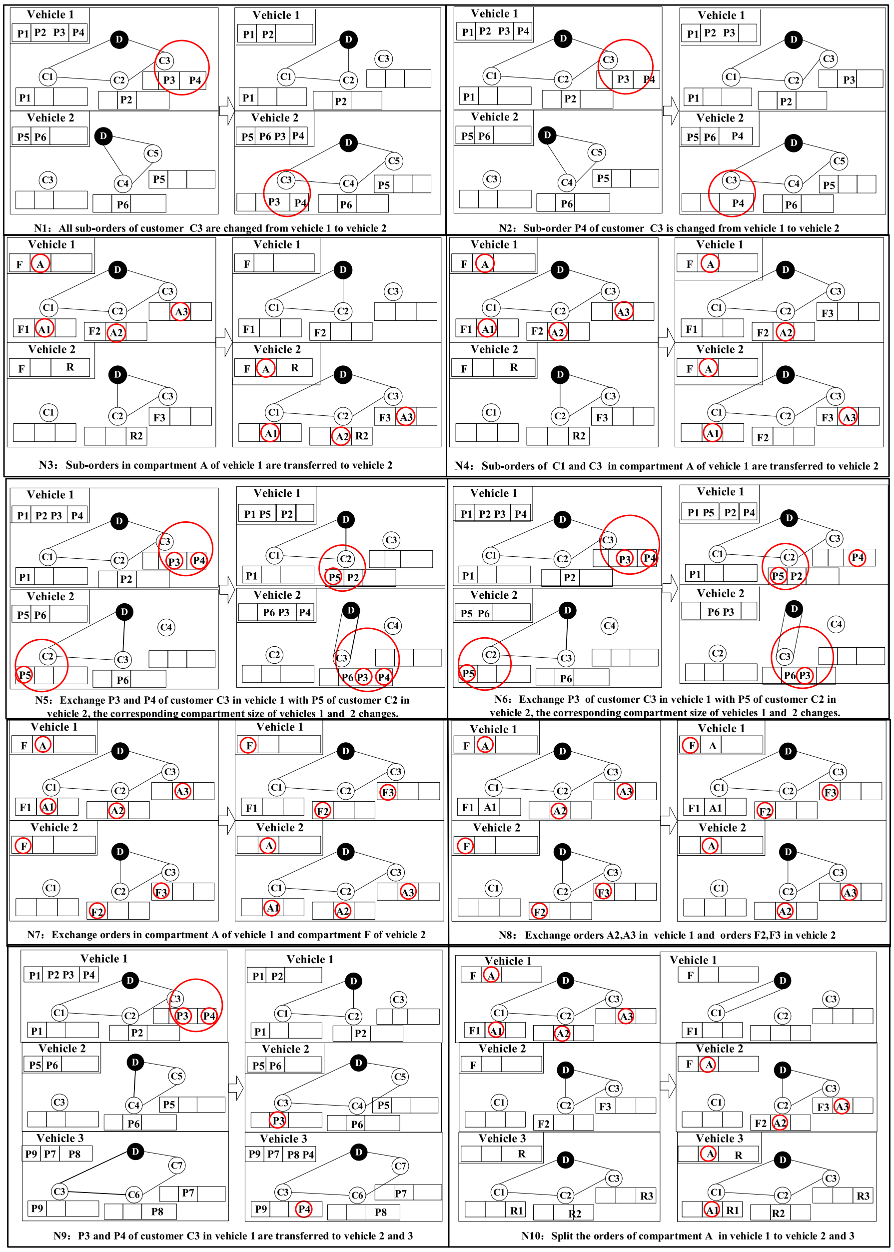

FIGURE 2. Illustration of 10 different neighborhood structures.

Solomon's data sets. Therefore, a special set on the proportion of different products is needed when constructing the test case. According to customer demand in real life, the proportion of products placed in three different compartments is set to Frozen: Refrigerated: Ambient = 0.1:0.65:0.25 [33]. The number of locations is 25, 50, and 100, respectively. The demand for products is counted by units of pieces. Moreover, it is assumed that every item occupies the same space in the vehicle. Table 3 shows the parameter set for the improved SA algorithm. Better optimization results are obtained through random tests in the range of commonly used parameters in the general SA algorithm.

Three sets of numerical experiments are presented to evaluate the efficiency of the proposed VNSA algorithm and the innovation of the concept that each compartment has a flexible temperature range with a defined upper bound and lower bound. In the first set, the VNSA algorithm is applied to flexible size and fixed-size problem instances. The second set of experiments is a cost comparison between split delivery and non-split delivery. In the third set of experiments, the performances of the VNSA algorithm and the variable neighborhood search (VNS) algorithm on the total cost and the solution time are examined. The maximum number of iterations of the VNS algorithm is set to 1000.

TABLE 2. Neighborhood structure considering a split between order and compartment.

Number	Structure	Description
N1	Complete-order-shift	Remove all suborders of customer *j* from one vehicle to others
N2	Partial-order-shift	Remove partial suborders of customer *j* from one vehicle to others
N3	Complete-compartment-shift	Remove all orders of one compartment in one vehicle to others
N4	Partial-compartment-shift	Remove partial orders of one compartment in one vehicle to others
N5	Complete-order-swap	Swap all suborders of customer *j* in in any two vehicles, the species of items can be different
N6	Partial-order-swap	Swap partial suborders of the customer *j* in any two vehicles, the species of items can be different
N7	Complete-compartment-swap	Swap all orders of one compartment in any two vehicles, the species of items may be different
N8	Partial-compartment-swap	Swap partial orders of one compartment in any two vehicles, the species of items may be different
N9	Complete-order-split	Split orders of customer *j* in one vehicle and insert them into any other two vehicles
N10	Complete-compartment-split	Split orders of customer *j* in one compartment of one vehicle and insert them into any other two vehicles

```
Input: data, number of neighborhood structures k^max
do generate an initial solution x_0 based on the solution set
x^GA ; set x^now := x_0 , x* := x_0 , iter := 0 , T := T_0 ,
neighborhood structure index k to k := 1;
  while iter ≤ iter^max and T ≥ T_end
    select a neighbor m randomly, apply local search 2-
    opt, 2-opt* to m and determine a solution x_0^1;
      if obj(x_0^1) ≤ obj(x_0) , then
        x* := x_0^1; k := 1;
          if obj(x*) > obj(x^now) or RANDOM (0,1)
          ≤ P(obj(x^now) − obj(x*), T) , then
            x* := x^now ;
        end if
      else
        k := k + 1
          if k := k^max + 1 , then
            k := 1;
          end if
      end if
    T = T * alpha
    iter = iter + 1;
  end while
Output: x* ;
```

FIGURE 3. Pseudo-code of the VNSA.

TABLE 3. List of parameters in numerical experiments.

Parameter	Value
MaxGeneration	200
PopSize (Population size)	100
Pc (Crossover rate)	0.6
Pm (Mutation rate)	0.05
T_0 (Initial temperature)	$1e^9$
Alpha (Cooling factor)	0.99
$iter^{\max}$	100

TABLE 4. Fixed and flexible compartment size range.

	r_{kp}	Frozen	Ambient	Refrigerated
Fixed	(a)	0.33	0.33	0.34
	(b)	Set the ratio by the total demand of customers		
Flexible	(c)	[0.1,0.3]	[0.2,0.4]	[0.5,0.7]
	(d)	[0.3,0.7]	[0,0.2]	[0.2,0.7]
	(e)	[0.2,0.5]	[0.2,0.5]	[0.2,0.5]
	(f)	[0,1]	[0,1]	[0,1]

A. EXPERIMENTS WITH FLEXIBLE SIZE AND FIXED-SIZE PROBLEM INSTANCES

Regarding the fabrication of refrigerated trucks, the side door size is specified to allow one person to pass, with a size of about 0.8–1 m. The location of the side door varies across brands and models. The most popular refrigerated truck model has two side doors. In this subsection, an experiment is described where two sets of fixed compartment sizes and four sets of compartment capacities with flexible ranges are used as shown in Table 4. These are set by brands of one-driving-two vehicles. For the set of fixed compartment sizes, (a) is given by actual measurement and (b) is determined based on the ratio of customer demand for different products.

Under each of the six different compartment size specifications, the total transportation cost and the number of vehicles used are solved. To evaluate the superiority of the compartment capacity with flexible ranges, four flexible capacity ranges are compared against compartments with fixed capacity.

TABLE 5. Comparison of the cost and number of refrigerated trucks on range (c) and fixed capacities (a) and (b).

Instance	Flexible range(c)		(a)		(b)		Gap (%)			
	Cost	$\|K\|$	*Cost*	$\|K\|$	*Cost*	$\|K\|$	*Cost(a)*	$\|K\|(a)$	*Cost(b)*	$\|K\|(b)$
C101_25	2515.3	3	3059.24	6	3444.46	5	17.78	50.00	26.98	40.00
C101_50	5310	5	7325.04	9	6516.69	7	27.51	44.44	18.52	28.57
C101_100	11544.46	10	16932.05	19	15731.2	15	31.82	47.37	26.61	33.33
R101_25	3244.95	2	3703.98	4	3347.97	3	12.39	50.00	3.08	33.33
R101_50	5867.1	4	7220.89	8	6210.25	4	18.75	50.00	5.53	0.00
R101_100	12631	8	14933.39	14	13488.54	9	15.42	42.86	6.36	11.11
R110_25	3386.9	2	3436.28	4	3465.52	2	1.44	50.00	2.27	0.00
R110_50	5584.06	5	7397.09	8	6713.03	4	24.51	37.50	16.82	-25.00
R110_100	12593.03	8	14817.91	15	14030.42	9	15.01	46.67	10.24	11.11
RC107_25	2390.66	3	4149.21	5	2711.68	3	42.38	40.00	11.84	0.00
RC107_50	4435.19	5	8066.65	10	9315.37	6	45.02	50.00	19.85	16.67
RC107_100	13036.01	10	16431.84	18	16834.45	15	20.67	44.44	18.47	33.33
C201_50	8521.31	2	8619.73	3	13717.37	2	1.14	33.33	8.52	0.00
C201_100	16464.49	3	17216.49	6	10882.8	3	4.37	50.00	2.20	0.00
R201_100	12405.41	3	12899.08	5	5965.13	3	3.83	40.00	9.56	0.00
R210_100	10509.14	3	11789.66	5	12720.7	3	10.86	40.00	3.43	0.00
RC201_50	5526.83	2	6752.1	3	9315.37	2	18.15	33.33	7.35	0.00
RC201_100	11957.96	3	12808.85	5	16834.45	3	6.64	40.00	6.00	0.00
Average							***17.65***	***43.89***	***11.31***	***10.14***

Table 5 lists all results for the cost and the number of refrigerated trucks used under fixed capacity specifications (a) and (b) as well as the flexible range (c). It also presents the cost percentage savings of the number of refrigerated trucks used for flexible range (c) compared to the fixed capacity specifications (a) and (b). Across all 18 instances shown in Table 5, the transportation costs for flexible range (c) are superior to the costs for the fixed sizes (a) and (b). The average cost saving percentage for flexible range (c) is 17.65% compared with the fixed capacity (a). Flexible range (c) excels in terms of truck loading rate when using a smaller number of trucks than fixed capacity schemes. The average saving is 43.89% compared with fixed capacity scheme (a) and 10.14% compared with fixed capacity scheme (b). The refrigerated compartments with flexible size ranges can effectively improve the logistics distribution efficiency and reduce the total transportation cost.

Table 6, Table 7, and Table 8 present the same comparison for flexible ranges (d), (e), and (f), respectively. All instances are solved by the VNSA algorithm proposed in Section IV.

For all 18 instances shown in Table 6 and Table 8, a similar observation can be made, i.e., that an average optimization ratio for a flexible compartment range is desirable when compared to the two fixed loading methods. However, for the 18 instances shown in Table 7, while the average optimization ratio for flexible compartment range is worse than the fixed loading method, the average cost is superior. Thereby, when vehicles are sufficient, carriers can still select the distribution with flexible compartment range to reduce the total cost.

The results of this set of flexible size and fixed-size problem instances demonstrate a reduction of the total cost with different loading methods for the MTJD problem over vehicles with fixed compartments. The efficiency of the flexible range (c) dominates other flexible ranges. Carriers can set the position of the door by referring to range c when initially customizing the vehicle. To show the performance of the VNSA, Figure 3 and Figure 5 present the cost evolution and the corresponding roadmap for instance R101-50 of range (c). Furthermore, carriers can have a variety of practical choices based on the actual total demand of customers, their current vehicle availability, and the estimated cost.

B. EXPERIMENTS FOR SPLIT AND NON-SPLIT ORDERS WITH FLEXIBLE SIZE INSTANCES

In the previous set of numerical experiments, all results are obtained for the case where orders can be split. To ensure the effectiveness of order splitting, a second set of numerical experiments is performed where the flexible compartment size range is set to the range (c). In addition to the "SPLIT" scenario, the "NON-SPLIT" scenario is also examined where all orders of a certain customer must be completed by the same vehicle. The results are shown in Table 9.

TABLE 6. Comparison of the cost and number of refrigerated trucks on range (d) and fixed capacities (a) and (b).

Instance	Flexible range(d)		(a)		(b)		Gap (%)			
	Cost	|*K*|	*Cost*	|*K*|	*Cost*	|*K*|	*Cost(a)*	|*K*|*(a)*	*Cost(b)*	|*K*|*(b)*
C101_25	2567.84	3	3059.24	6	3444.46	5	16.06	50.00	25.45	40.00
C101_50	5325.05	6	7325.04	9	6516.69	7	27.30	33.33	18.29	14.29
C101_100	11656.65	11	16932.05	19	15731.2	15	31.16	42.11	25.90	26.67
R101_25	3464.89	2	3703.98	4	3347.97	3	6.45	50.00	-3.49	33.33
R101_50	6001.07	5	7220.89	8	6210.25	4	16.89	37.50	3.37	-25.00
R101_100	13894.38	11	14933.39	14	13488.54	9	6.96	21.43	-3.01	-22.22
R110_25	3167.43	2	3436.28	4	3465.52	2	7.82	50.00	8.60	0.00
R110_50	6004	5	7397.09	8	6713.03	4	18.83	37.50	10.56	-25.00
R110_100	12968.39	11	14817.91	15	14030.42	9	12.48	26.67	7.57	-22.22
RC107_25	2875.29	3	4149.21	5	2711.68	3	30.70	40.00	-6.03	0.00
RC107_50	4804.03	6	8066.65	10	9315.37	6	40.45	40.00	13.18	0.00
RC107_100	13538.6	11	16431.84	18	16834.45	15	17.61	44.44	15.33	26.67
C201_50	7986.78	2	8619.73	3	13717.37	2	7.34	33.33	14.26	0.00
C201_100	16419.26	4	17216.49	6	10882.8	3	4.63	33.33	2.47	-33.33
R201_100	12395.39	3	12899.08	5	5965.13	3	3.90	40.00	9.64	0.00
R210_100	10806.23	3	11789.66	5	12720.7	3	8.34	40.00	0.70	0.00
RC201_50	5698.59	2	6752.1	3	9315.37	2	15.60	33.33	4.47	0.00
RC201_100	11400.26	3	12808.85	5	16834.45	3	11.00	40.00	10.38	0.00
Average							***15.75***	***38.19***	***9.39***	***5.10***

TABLE 7. Comparison of the cost and number of refrigerated trucks on range (e) and fixed capacities (a) and (b).

Instance	Flexible range(e)		(a)		(b)		Gap (%)			
	Cost	|*K*|	*Cost*	|*K*|	*Cost*	|*K*|	*Cost(a)*	|*K*|*(a)*	*Cost(b)*	|*K*|*(b)*
C101_25	2808.32	4	3059.24	6	3444.46	5	8.20	33.33	18.47	20.00
C101_50	5604.35	7	7325.04	9	6516.69	7	23.49	22.22	14.00	0.00
C101_100	13345.3	14	16932.05	19	15731.2	15	21.18	26.32	15.17	6.67
R101_25	3130.63	3	3703.98	4	3347.97	3	15.48	25.00	6.49	0.00
R101_50	6865.2	6	7220.89	8	6210.25	4	4.93	25.00	-10.55	-50.00
R101_100	13749.67	11	14933.39	14	13488.54	9	7.93	21.43	-1.94	-22.22
R110_25	3167.22	3	3436.28	4	3465.52	2	7.83	25.00	8.61	-50.00
R110_50	6705.22	6	7397.09	8	6713.03	4	9.35	25.00	0.12	-50.00
R110_100	13744.72	12	14817.91	15	14030.42	9	7.24	20.00	2.04	-33.33
RC107_25	3019.84	4	4149.21	5	2711.68	3	27.22	20.00	-11.36	-33.33
RC107_50	6850.3	8	8066.65	10	9315.37	6	15.08	20.00	-23.80	-33.33
RC107_100	14601.82	14	16431.84	18	16834.45	15	11.14	22.22	8.68	6.67
C201_50	7638.96	2	8619.73	3	13717.37	2	11.38	33.33	18.00	0.00
C201_100	16056.63	5	17216.49	6	10882.8	3	6.74	16.67	4.62	-66.67
R201_100	11611.64	4	12899.08	5	5965.13	3	9.98	20.00	15.35	-33.33
R210_100	10563.05	4	11789.66	5	12720.7	3	10.40	20.00	2.94	-33.33
RC201_50	6020.96	3	6752.1	3	9315.37	2	10.83	0.00	-0.94	-50.00
RC201_100	12328.78	5	12808.85	5	16834.45	3	3.75	0.00	3.08	-66.67
Average							***11.79***	***20.86***	***3.83***	***-27.16***

TABLE 8. Comparison of the cost and number of refrigerated trucks on range (f) and fixed capacities (a) and (b).

Instance	Flexible range(f)		(a)		(b)		Gap (%)			
	Cost	|*K*|	*Cost*	|*K*|	*Cost*	|*K*|	*Cost(a)*	|*K*|*(a)*	*Cost(b)*	|*K*|*(b)*
C101_25	2487.38	3	3059.24	6	3444.46	5	18.69	<u>*50.00*</u>	27.79	40.00
C101_50	5804.19	5	7325.04	9	6516.69	7	20.76	44.44	10.93	28.57
C101_100	13969.06	10	16932.05	19	15731.2	15	17.50	47.37	11.20	33.33
R101_25	3277.52	2	3703.98	4	3347.97	3	11.51	<u>*50.00*</u>	2.10	33.33
R101_50	6396.68	4	7220.89	8	6210.25	4	11.41	<u>*50.00*</u>	-3.00	0.00
R101_100	12290.6	8	14933.39	14	13488.54	9	17.70	42.86	8.88	11.11
R110_25	3030.65	2	3436.28	4	3465.52	2	11.80	<u>*50.00*</u>	12.55	0.00
R110_50	5838.58	4	7397.09	8	6713.03	4	21.07	<u>*50.00*</u>	13.03	0.00
R110_100	11931.54	8	14817.91	15	14030.42	9	19.48	46.67	14.96	11.11
RC107_25	2649.81	3	4149.21	5	2711.68	3	<u>*36.14*</u>	40.00	2.28	0.00
RC107_50	5276.65	5	8066.65	10	9315.37	6	<u>*34.59*</u>	<u>*50.00*</u>	4.64	16.67
RC107_100	12086.18	9	16431.84	18	16834.45	15	26.45	<u>*50.00*</u>	24.41	40.00
C201_50	8401.73	2	8619.73	3	13717.37	2	2.53	33.33	9.81	0.00
C201_100	16880.15	3	17216.49	6	10882.8	3	1.95	<u>*50.00*</u>	-0.27	0.00
R201_100	12222.8	3	12899.08	5	5965.13	3	5.24	40.00	10.90	0.00
R210_100	10499.61	3	11789.66	5	12720.7	3	10.94	40.00	3.52	0.00
RC201_50	6523.41	2	6752.1	3	9315.37	2	3.39	33.33	-9.36	0.00
RC201_100	12176.23	3	12808.85	5	16834.45	3	4.94	40.00	4.28	0.00
Average							***15.34***	***44.89***	***8.26***	***11.90***

TABLE 9. Comparison of SPLIT and NON-SPLIT orders.

Instance	SPLIT			NON-SPLIT			Gap	
	Cost	*Time*	|*K*|	*Cost*	*Time*	|*K*|	*Cost*	|*K*|
C101_25	2515.3	43.36	3	2652.6	42.29	3	5.18%	0.00%
C101_50	5310	58.08	5	5511.23	60.98	5	3.65%	0.00%
C101_100	11544.46	90.27	10	12501.61	87.29	10	7.66%	0.00%
R101_25	3244.95	44.59	2	3688	44.72	2	<u>*12.01%*</u>	0.00%
R101_50	5867.1	57.56	4	6450.78	57.2	5	9.05%	20.00%
R101_100	12631	89.43	8	13410.35	85.53	8	5.81%	0.00%
R110_25	3386.9	43.92	2	3559.56	48.31	2	4.85%	0.00%
R110_50	5584.06	60.41	5	5860.94	58.07	5	4.72%	0.00%
R110_100	12593.03	89.23	8	12992.46	84.51	8	3.07%	0.00%
RC107_25	2390.66	38.85	3	2435.96	39.14	3	1.86%	0.00%
RC107_50	4435.19	56.98	5	4489.22	54.71	5	1.20%	0.00%
RC107_100	13036.01	91.75	10	14081.53	88.5	10	7.42%	0.00%
C201_50	8521.31	79.26	2	9028.79	78.54	2	5.62%	0.00%
C201_100	16464.49	125.45	3	16982.54	123.24	3	3.05%	0.00%
R201_100	12405.41	139.5	3	13814.22	134.07	3	<u>*10.20%*</u>	0.00%
R210_100	10509.14	137.46	3	11264	134.58	3	6.70%	0.00%
RC201_50	5526.83	92.26	2	6155.99	87.54	2	<u>*10.22%*</u>	0.00%
RC201_100	11957.96	128.24	3	12287	122.61	3	2.68%	0.00%
Average							**5.83%**	**1.11%**

Across the 18 sets of numerical experiments shown in Table 9, an effective reduction of total transportation costs can be achieved when a customer's product demands can be fulfilled by different vehicles. The average distribution cost can be reduced by 5.83% when the splitting of orders is allowed.

C. EXPERIMENTS FOR THE IMPROVED SA AND VNS WITH SPLIT ORDERS

To evaluate the efficiency of the proposed SA algorithm with variable neighborhoods, the variable neighborhood algorithm was set as comparison algorithm. In this section, the result of another set of numerical experiments is shown. The flexible

TABLE 10. Comparison between VNSA and VNS.

Instance	VNSA			VNS			Gap	
	Cost	Time	|K|	Cost	Time	|K|	Cost	Time
C101_25	2515.3	43.36	3	2722.7	49.7	3	7.62%	12.76%
C101_50	5310	58.08	5	5446.82	64.07	5	2.51%	9.35%
C101_100	11544.46	90.27	10	12203.25	97.04	10	5.40%	6.98%
R101_25	3244.95	44.59	2	3660.43	51.09	2	11.35%	12.72%
R101_50	5867.1	57.56	4	6018.19	63.21	5	2.51%	8.94%
R101_100	12631	89.43	8	13748.71	95.39	8	8.13%	6.25%
R110_25	3386.9	43.92	2	3544.66	50.08	2	4.45%	12.30%
R110_50	5584.06	60.41	5	5973.26	62.94	5	6.52%	4.02%
R110_100	12593.03	89.23	8	12764.13	95.04	8	1.34%	6.11%
RC107_25	2390.66	38.85	3	2449.65	48.98	3	2.41%	20.68%
RC107_50	4435.19	56.98	5	4532.49	63.68	5	2.15%	10.52%
RC107_100	13036.01	91.75	10	13578.6	99.14	10	4.00%	7.45%
C201_50	8521.31	79.26	2	9580.09	84.71	2	11.05%	6.43%
C201_100	16464.49	125.45	3	16951.73	133.87	3	2.87%	6.29%
R201_100	12405.41	139.5	3	13922.86	143.98	3	10.90%	3.11%
R210_100	10509.14	137.46	3	10879.48	141.99	3	3.40%	3.19%
RC201_50	5526.83	92.26	2	5741.89	95.65	2	3.75%	3.54%
RC201_100	11957.96	128.24	3	12534.82	132.55	3	4.60%	3.25%
Average							**5.28%**	**7.99%**

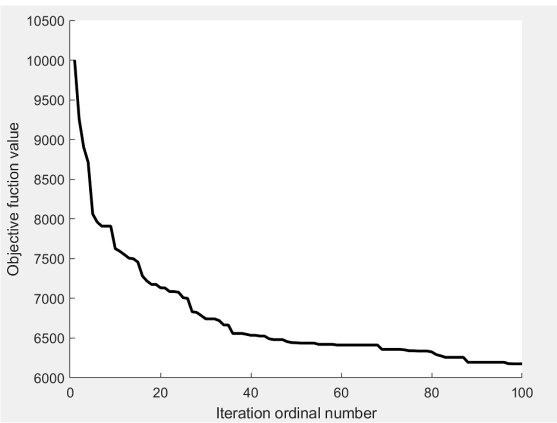

FIGURE 4. Cost evolution for instance R101-50 of range (c).

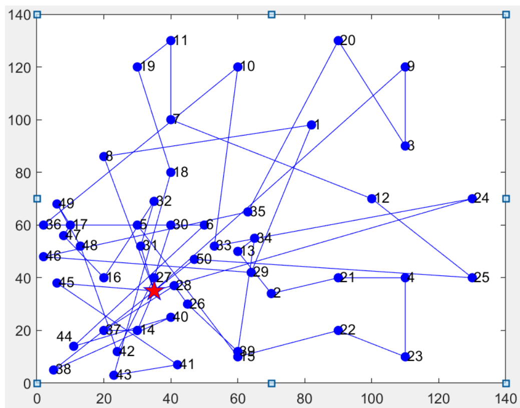

FIGURE 5. Roadmap in instance R101-50 of range (c).

compartment size range is set to range (c) and the proposed SA algorithm (VNSA) is used to solve 18 sets of instances. For comparison, the VNS algorithm is used under the same neighborhood structures to solve 18 sets of instances. In the experiment, splitting the orders into suborders is allowed. Table 10 shows the specific results.

Table 10 shows that the VNSA algorithm results in solutions that are superior to VNS in terms of total distribution cost for the same neighborhood structures. The average distribution cost can be reduced by 5.28%. Regarding algorithm efficiency, the proposed VNSA algorithm clearly excels by an average of 7.99% when compared with the VNS algorithm. Moreover, Figure 6 shows the speed of iteration of the two algorithms, where the VNSA has a faster convergent speed than the VNS.

VI. CONCLUSION

This paper presents the formulation of a MTJD problem (and associated model) of fresh agricultural products. By considering a flexible compartment range with a specified upper

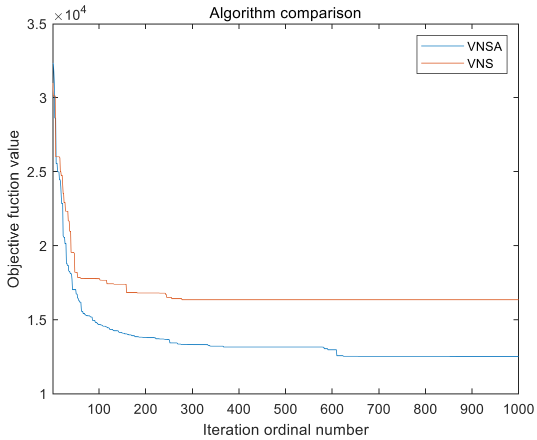

FIGURE 6. Cost evolution of VNSA and VNS for instance RC107-100 of range (c).

bound and lower bound and partial order-splitting, this problem differs from any other problem that was previously discussed in the literature. This paper formulates two models for MTJD problems with or without considering delivery time requirements. A solution method is proposed for obtaining the distribution plan based on current vehicle availability and estimated cost. In certain cases, increasing the number of vehicles to be used for delivery may not lead to an increase in total costs. The considered problem is applicable to situations in which vehicle fleet capacity is limited.

The main contributions of this paper are summarized in the following: (1) multi-temperature compartments are considered for vehicles where the mechanical freezing-plate cannot be placed at the side door. Both upper bound and lower bound are defined, which differs from discretely flexible compartment sizes or continuously flexible compartment sizes; (2) a model is formulated for a new modification of the MTJD problem with a limited flexible compartment size range, a mixed time window, and partial order-splitting which is more realistic and practical; (3) a solution procure is designed for this modification of the MTJD problem and the performance of the improved algorithm is examined.

Numerical experiments are presented to show the economic benefits of the models and algorithms proposed in this paper. The results indicate that different loading and distribution strategies significantly influence distribution efficiency. For the MTJD problem with flexible size of each compartment, the proposed design effectively increases the loading capacity, thereby improving the efficiency of cold-chain logistics and optimizing the distribution cost. When ensuring that the demands of all customers are satisfied, this model allows orders of different products to be split into suborders. Thus, the vehicle loading rate can be improved and the total distribution costs can be reduced. The improved SA algorithm performs well in solving the MTJD problem. It can effectively improve both solution efficiency and cost effect, which can provide effective decision support for carriers.

As with any research, this study is subject to limitations, which provide avenues for future research. In this study, only one type of vehicle was considered (the mechanical refrigerated vehicle). In fact, the cold storage refrigerator car has also been used for such problems in recent years. In future research, other important features can also be considered such as a fleet of heterogeneous vehicles. This would allow to focus on the collaborative distribution optimization of fresh products under multiple vehicle types, which not only differ by capacity but also by other vehicle attributes. Moreover, routing optimization of various speeds and more efficient and effective meta-heuristics can be explored by future research.

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