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APPLICATION OF MULTI-TEMPERATURE REFRIGERATED CONTAINER TO IMPROVE THE DISTRIBUTION OF COLD LOGISTICS

Yuh-Jen CHO
Assistant Professor
Department of Transportation Technology and Logistics Management
Chung Hua University
707, Sec. 2, Wu Fu Rd., Hsin Chu,
300, Taiwan, R.O.C.
Fax: +886-3-5186545
E-mail: yjcho@chu.edu.tw

Chang-Chun LI
Master (In Army)
Institute of Technology Management
Chung Hua University
707, Sec. 2, Wu Fu Rd., Hsin Chu,
300, Taiwan, R.O.C.
Fax: +886-3-5186545
E-mail: m9103065@chu.edu.tw

Abstract: The multi-temperature refrigerated container is a bran-new technique, which can be setup on different temperatures, and preserve goods from losing temperature within almost 24 hours. Consequently, carriers can utilize such a container to hold and deliver different temperature goods to customers in general trucks. This paper formulates the above situation to the Multi-temperature Refrigerated Container Vehicle Routing Problem (MRCVRP), and proposes a two-stage heuristic which consists of modified savings algorithms to construct the initial solution and improve it by sequentially executing four interchange heuristics. To compare the performance of the MRCVRP with that of the classical VRP, a bank of 60 instances, modified from the Solomon's VRPTW benchmark instances, is adopted. Computational results reveal that MRCVRP generates significantly lower routing distance than VRP. Such a finding identifies that the MRCVRP could offer an effective and efficient alternative to improve the performance of multi-temperate fresh-keeping delivery service and cold logistics.

Key Words: cold logistics, multi-temperature Refrigerated Container, heuristic algorithm

1. INTRODUCTION

Reports indicate that the world's demand for perishable goods, such as refrigerated foods, fresh fruits and flowers, rose from 42 million tons in 1987 to 44 million tons in 1990 and is likely to reach 53 million tons by 2000 (Donna, 1992). According to the statistics from the Industrial Economics and Knowledge Center (IEK) under Industrial Technology Research Institute (ITRI), the Taiwan's market share of refrigerated foods varies in retail channels. As shown in Table 1, the total market scale of the refrigerated foods already exceeded 200 billion NT dollars in 2000 (Kuo, 2004a). The fast increasing demand for refrigerated foods means profits for the manufacturers and marketers of refrigerated transport equipment. Moreover, such an increase motivates the growth of needs for cold logistics distribution.

In order to keeping good quality of refrigerated foods, cold logistics carriers have to adopt optimal temperature control on multi-temperature commodities in the process of supply, storage and delivery. With regard to Taiwan's present-day mechanical engine-driven compressor freezer trucks are concerned, the trucks are frequently forced to idle their engines due to the traffic congestion that is so common in Taiwan, which means that the truck engines are often unable to deliver enough power to maintain freezing temperatures. As a consequence, foods cannot be kept in an appropriate low-temperature state during transport, which affects the foods' quality. In addition, the stores along distribution routes in crowded Taiwan are often excessively close to each other, so that the warm air that enters a freezer truck whenever the door is opened to make a delivery does not have time to cool off before the next delivery.

Table 1. Sales of Refrigerated Food via Retail Channels in Taiwan (million NT dollars)

Year	Modern Retail Channels					Restaurants	Total
	Department Stores	Super-markets	Convenience Stores	Hyper-markets	Others		
1998	2,350	21,671	29,682	32,459	12,875	42,444	141,481
1999	2,563	22,716	35,393	38,801	13,262	60,704	173,441
2000	2,828	22,885	38,009	45,571	13,823	82,138	205,345

Source: IEK, ITRI (Kuo, 2004a)

Furthermore, refrigerated transport requires carriers to make high capital investments in equipment. For example, the sale price of a 3.5 tons freezer truck is about 800,000 NT dollars and that of a 3.5 tons general truck is 650,000 NT dollars at most. Additionally, most of the freezer trucks currently in use are equipped to carry only low-temperature foods with the same product temperature, so that different types of low-temperature foods must be distributed in different deliveries, causing reduced vehicle use efficiency, or two or more freezer trucks must be purchased for the transfer of goods with different product temperatures, which increases investment and operating costs. Therefore, how to distribute multi-temperature goods with lower cost raises an important issue in the cold logistics.

Recently, the Energy and Resources Laboratories (ERL) of the ITRI has developed an innovational technology, multi-temperature refrigerated transport system with no-drive refrigeration, which enables to meet the needs of Taiwan's geography, climate, and societal conditions (Kuo, 2003). The purpose of this study is to develop an extended vehicle routing model based on the usage of the multi-temperature refrigerated transport system. We name this model as the Multi-temperature Refrigerated Container Vehicle Routing Problem (MRCVRP). Additionally, a heuristic method is proposed for solving the MRCVRP and sixty instances of four different scenarios are generated to identify the performance of the MRCVRP and the potential of multi-temperature refrigerated transport system to the cold logistics.

This article is organized as follows. Section 2 surveys the technology of the multi-temperature refrigerated transport system and related researches on cold logistics. Section 3 presents the mathematical formulation of the MRCVRP. Then, Section 4 describes the two-stage heuristic for the MRCVRP. Experimental designs and results are reported in Section 5. Finally, Section 6 concludes our findings and suggests several directions of further research.

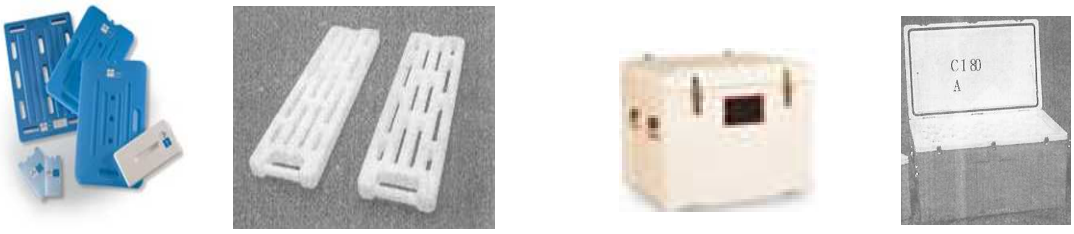
2. LITERATURE REVIEW

Even though several literatures discussed the R&D of multi-temperature refrigerated transport system (Lai, 2003; Kuo, 2003; Kuo, 2004a; Kuo, 2004b; OLIVO, 2004) and the distribution models of cold logistics (Tseng, 1998; Wang, 2000; Wang, 2001; Hung, 2003; Tarantitlis *et al.*, 2004), the study on the fleet routing of the multi-temperature refrigerated transport does not emerge.

2.1 Technologies of Multi-temperature Refrigerated Transport System

Equipment used in refrigerated cargo transport is forever evolving. Lai (2003) studied a multi-temperature logistic system with energy storage materials which can store or release thermal energy and in the mean time change their phase states at different temperatures. The energy storage materials which can release (or absorb) thermal energy during freezing (or melting), can be either phase change single-inorganic component or multi-inorganic component with large specific heat capacity, high heat transfer rate, desired transition temperature and repeatable usage. In this research, the eutectic property and heat capacity of the single- or multi-component inorganic phase change materials with the large latent heat and melting points between -35℃ ~ 90℃ were experimentally determined. The best practical design and manufacturing parameters as well as the best operating parameters were studied through the comparison of simulation results with experimental results.

The multi-temperature no refrigeration drive refrigerated transport system (MRTS) developed by the ERL uses multi-temperature cold storage and cold release technology (Kuo, 2003). MRTS possesses an automatic cold augmentation design, a cold energy conversion design, a shipping container accommodation design, a high-efficiency eutectic plate (see Figure 1a), and a multi-temperature refrigerated container structure (see Figure 1b). The eutectic plate is to make use of freezing apparatus for pre-cooling, and the multi-temperature refrigerated container is to offer proper cubage for the placement of articles and eutectic plates. Placed in the top part of container, the eutectic plate releases a constant cooling capacity previously accumulated in the cold room during the freezing process. Eutectic refrigeration allows the required temperature to be maintained 24 hours and more for chilled products as well as for frozen (OLIVO, 2004).



(a) Eutectic plate (b) Multi-temperature refrigerated container

Figure 1. Major Components of the MRTS

These MRTS technologies ensure that the new-type refrigerated transport system can be used with standardized refrigerated shipping containers. The ability to carry products with different temperatures not only reduces the number of delivery trips needed, but also keeps delivery costs lower than when ordinary chilled trucks are used. MRTS has been actually used to make deliveries to coffee shop chains like Starbucks and IS coffee shops, as well as low-temperature shipments and home deliveries by Ta Jung Transportation Inc. The only similar system is used in Japan, but the small-scale Japanese system relies on costly and non-reusable dry ice to cool cargo containers during transshipment (Kuo, 2004b).

2.2 Studies and Applications on Cold Logistics

Tseng (1998) transferred the cold delivery to a dynamic vehicle routing problem (DVRP), which considers the varieties of intersection signals and real-time information at night and in the urban area. This research developed an algorithm to determine the optimal vehicle routes.

Results indicate that applying this heuristic algorithm to dynamic vehicle routing problems can improve night delivery efficiency and decline logistics costs.

Wang (2000) investigated the planning of vehicle routing of a frozen food distribution center, and built a mathematical model which employs penalty functions to reflect the characteristic of frozen food and time window constraints. Moreover, a two-stage algorithm is proposed to solve the VRPTW. In the first stage, genetic algorithm is used to cluster customers with respect to each vehicle. The second stage finds an optimal routing for each cluster, and the results are fed back to the first stage as a performance measurement of the current clustering.

In Wang (2001), two performance indexes were applied to measure the scheduling operation of a refrigerated food distribution center: (1) the cost of transportation, and (2) the penalty cost due to violating customers' delivery time windows. Both hard time windows and soft time windows were adopted to build the VRPTW model. This resultant model has an embedded structure to decompose the original problem into a clustering master problem and many mutually independent routing sub-problems. In the solving of the master problem, a genetic algorithm is employed. As for the solving of sub-problems, a heuristic algorithm is formulated.

Hung (2003) presented a Stochastic Vehicle Routing Problem with Time Window (SVRPTW) model for refrigerated food. The objective function of the SVRPTW model aims at minimizing the sum of transportation cost, inventory cost, energy cost and penalty cost as related to violating time windows. This study formulated a time-dependent fresh food deteriorating function, calculated the probability of deterioration occurrences and evaluated how much loss it causes. Furthermore, Hung (2003) developed algorithms to solve two SVRPTW models with and without considering the time-varying travel time. Results of this study reveals that inventory loss and energy cost influence total distribution cost of refrigerated distribution significantly.

Tarantitlis *et al.* (2004) discussed on how to efficiently deliver perishable foods, such as milk, fresh fruits and vegetable and meat. A model of Heterogeneous Fixed Fleet Vehicle Routing Problem (HFFVRP) was proposed to get the minimum transportation cost. In addition, a meta-heuristic approach, Back-tracking Adaptive Threshold Accepting (BATA), is designed to solve the HFFVRP efficiently.

Summarily, most of previous researches considered the distribution of refrigerated goods as the VRPTW. Although that the requirement of time window from customers must be satisfied, it does not guarantee that the temperature of goods is keeping on the proper condition during the delivery. Therefore, effective solutions for cold logistics and transportation are necessary.

3. DEFINITION AND FORMULATION OF THE MRCVRP

As mentioned above, there is no literature which discusses on the fleet routing of multi-temperature refrigerated transport system. In this Section, we propose an extension of Vehicle Routing Problem (VRP), Multi-temperature Refrigerated Container Vehicle Routing Problem (MRCVRP) to generate the optimal routes of MRTS. The traditional VRP considers the capacity constraint of trucks and the demand of a single commodity. The proposed MRCVRP has to simultaneously satisfy the capacity constraints of refrigerated containers and trucks for loading multiple commodities, which are classified by their keeping temperature. In addition, each refrigerated container has to assign a specific temperature for handling relative commodities.

The MRCVRP can be described as follows. Given a set of customers with demands for different temperature goods, the fleet of trucks must depart from the central depot, sequentially deliver (pick up) goods to (from) all customers under the restrictions on capacity of refrigerated containers and trucks, and finally return to depot. The objective of MRCVRP is to minimize total cost consisting of trucks usage, refrigerated containers usage, and routes traveling. The other assumptions and restrictions are:

1. Demands for goods under different temperatures from a single customer should have to be served by a single truck, that is, partial delivery (pick-up) would not be permitted. This character of undividable demand is always reasonable in practical operation;

2. The capacity of refrigerated containers is identical. Each refrigerated container is able to assign a specific temperature according to the contents in it;

3. Goods could be separated to several refrigerated containers with the same temperature but all in an identical truck while overall demand for goods under a certain temperature exceeds the volume of a single refrigerated container;

4. The number of refrigerated containers that a truck can load is fixed. Each truck is available for just once. In order to obtain feasible solutions, the numbers of available trucks and refrigerated containers are supposed to be unlimited; and

5. The constraint of time windows to serve customers is not considered into the pioneering MRCVRP model.

The MRCVRP can be stated mathematically as follows. Where, $M = \{1, 2, \ldots, m\}$, set of the sorts of commodities, each kind of commodity is in a specific temperature level; $N = \{0, 1, 2, \ldots, n\}$, set of nodes (0 refers to the depot, and 1 ~ n refer to customers); $V = \{1, 2, \ldots, v\}$, set of vehicles; c_{ij} = traveling cost (distance or time) of arc (i, j); d_{hi} = demand for h kind of commodity of customer i; f = fixed cost of a vehicle; g = fixed cost of a refrigerated container; p = maximum number of refrigerated containers could be put into a vehicle; q = fixed capacity of a refrigerated container; x_{ijk} = 1 if arc (i, j) is traversed by vehicle k, 0 otherwise; y_{hk} = amount of refrigerated containers loading for h kind of commodity in vehicle k; z_i = variable to avoid sub-tour.

Minimize
$$f \cdot \sum_{j=1}^{n} \sum_{k=1}^{v} x_{0jk} + g \cdot \sum_{h=1}^{m} \sum_{k=1}^{\mathrm{v}} y_{hk} + \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{k=1}^{v} c_{ij} \cdot x_{ijk} \tag{1}$$

Subject to
$$\sum_{j=1}^{n} x_{0jk} \le 1 \qquad \forall\, k \in V \tag{2}$$

$$\sum_{j=0}^{n} x_{ijk} - \sum_{j=0}^{n} x_{jik} = 0 \qquad \forall\, i \in N, k \in V \tag{3}$$

$$\sum_{j=0}^{n} \sum_{k=1}^{v} x_{ijk} = 1 \qquad \forall\, i \in N \setminus \{0\} \tag{4}$$

$$\sum_{i=1}^{n}\left(d_{hi}\cdot\sum_{j=0}^{n}x_{ijk}\right)-q\cdot y_{hk}\leq 0 \qquad \forall\, h\in M, k\in V \tag{5}$$

$$\sum_{h=1}^{m}y_{hk}\leq p \qquad \forall\, k\in V \tag{6}$$

$$z_i-z_j+n\cdot x_{ijk}\leq n-1 \qquad \forall\, i\,\&\, j\in N\setminus\{0\}, k\in V \tag{7}$$

$$x_{ijk}=0\, or\, 1, y_{hk}\in I^{+}, z_i\geq 0 \qquad \forall\, h\in M, i\,\&\, j\in N, k\in V \tag{8}$$

The objective function (1) states that total cost should be minimized. Constraint set (2) states that each vehicle k could be used once at most. Constraint set (3) is the flow conservation equation requiring that each vehicle k leaves node i if and only if it enters that node. Constraint set (4) states that each customer i must be served by exactly one vehicle. Constraint set (5) indicts that the aggregated demand for h kind of commodity in vehicle k could not exceed the capacity of refrigerated containers assigned to load commodity h. Equation set (6) is the capacity constraint of vehicle k that no vehicle can load more refrigerated containers than its capacity permits. Constraint set (7) guarantees that sub-tour could be breaking. Equation set (8) defines the domain of variables respectively.

4. A TWO-STAGE HEURISTIC FOR THE MRCVRP

The MRCVRP model presents a double restriction of demand loadings, constraint set (5) for the amount of goods in a refrigerated container, and constraint set (6) for the amount of refrigerated container in a vehicle. Such a character makes that the MRCVRP is more difficult to solve than the VRP. Due that VRP is NP-hard, the MRCVRP is believed to be NP-hard, too. In this paper, we propose a two-stage heuristic method for the MRCVRP. The first stage aims to construct an initial feasible solution by using a modified savings-based algorithm. Then, this initial solution is improved by sequential implementations of several interchange-based heuristics.

4.1 Modified Savings Algorithm

The savings algorithm was originally proposed by Clarke and Wright (1964) to solve the VRP. Because of its simplicity and flexibility, savings algorithm has been modified to conquer other vehicle routing related problems, such as the Vehicle Routing Problem with Time Windows (VRPTW) in Solomon (1983) and the Fleet Size and Mix Vehicle Routing Problem (FSMVRP) in Golden et al. (1984). Initially, suppose that every customer is served individually by a separate vehicle. The savings algorithm calculates the savings value (s_{ij}) of every pair of nodes i and j according to Equation (9), and orders the savings list decreasingly.

$$s_{ij}=c_{i0}+c_{0j}-c_{ij} \tag{9}$$

Then, starting at the top of the list, savings algorithm iteratively merges two routes into a larger one by linking node-pair with the maximum savings unless the problem constraints (for example, the capacity constraint) are violated. Note that there are sequential and parallel versions to implement the merge of routes. The sequential savings algorithm constructs a specific route at one time until the capacity constraint of this route is violated, and the next new route is starting to merge. Oppositely, the parallel savings algorithm simultaneously develops several routes while merging.

In order to solve the MRCVRP, we modified the savings algorithm by combining the savings of capacity with original savings value (s_{ij}). Equations (10) and (12) describe the ideas of two new savings values. Equation (10) considers that it will save both the distance of route and the number of refrigerated container after merging two routes. Because of different unit and scale between routing distance and container's number, we multiply an adjusting term, the average arc distance (ac_{ij}) divided by the sorts of temperature level (m), by the savings of refrigerated container (cs_{ij}). Equation (11) works out the reduction of the number of refrigerated containers.

$$s_{ij}^{'} = s_{ij} + \frac{ac_{ij}}{m} \cdot cs_{ij} \tag{10}$$

$$cs_{ij} = \sum_{h=1}^{m} \left(\left\lceil \frac{d_{hi}}{q} \right\rceil + \left\lceil \frac{d_{hj}}{q} \right\rceil - \left\lceil \frac{d_{hi} + d_{hj}}{q} \right\rceil \right) \tag{11}$$

$$s_{ij}^{''} = s_{ij} - \frac{2 \cdot ac_{ij}}{m \cdot q} \cdot \sum_{h=1}^{m} \left[\mathrm{mod}\left(\frac{d_{hi} + d_{hj}}{q} \right) \right] \tag{12}$$

The other formula of the modified savings value is presented at Equation (12). The first part of the savings value is still the classical savings of distance, but the second part evaluates the residual capacity of all refrigerated containers in the merged vehicle. The negative sign before the second part means that the minimal residual capacity (i.e., make full use of the space) is wanted. In addition, an adjusted term, double average arc distance divided by the product of temperature levels by capacity of refrigerated container, is introduced to the second part. Algorithms adopt original savings formula, Equation (10) and Equation (12), separately named as SA0, SA1 and SA2.

4.2 Interchange Heuristics for Improvement

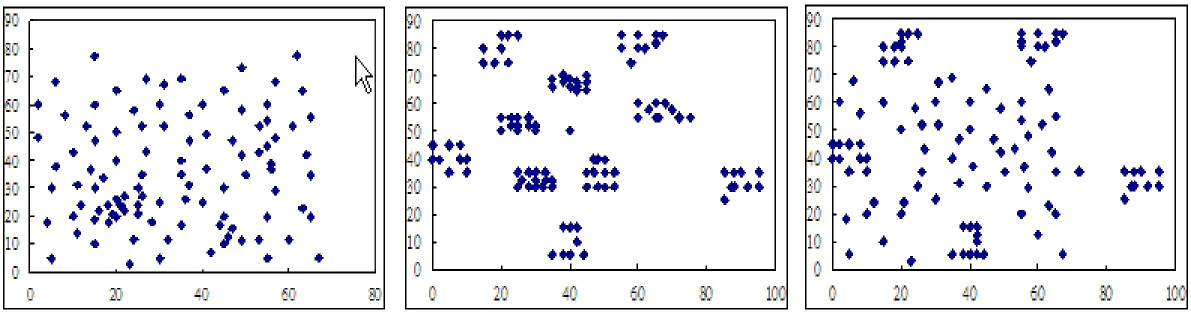
As the improvement-purposed modules of stage two, we select four interchange-based heuristics, 2_OPT intra-tour exchange, and (1_0), (1_1) and (2_1) inter-tour interchanges (Christofides and Eilon, 1969). While implementing of these three inter-tour interchanges, the feasibility of loaded goods by exchanging customers between two routes can not be violated. Furthermore, there are two rules to choose a neighbor solution for exchange, best-improvement and first-improvement. Hence, we adopt the best-improvement rule to execute the four interchange heuristics.

5. EXPERIMENTAL ANALYSIS

In order to identify the potentiality of proposed MRCVRP model in the improvement of the cold logistics, computational experiments on testing the performance of MRCVRP are reported. First, a set of MRCVRP instances are created in Section 5.1; then, a three-phase experiment are designed in Section 5.2 for testing; and finally, the results of the testing are summarized and analyzed in Section 5.3.

5.1 Bank of Testing Instances

As a new type of vehicle routing related problem, MRCVRP is still unavailable with a bank of benchmark instances or with a real-world case of cold logistics in any literature. Therefore, we generated a set of sixty MRCVRP instances based on the classical VRPTW instances. A set of 56 VRPTW instances which were originally generated by Solomon (1983), are classified as three types of geographical scatter of customers, i.e., C for clustering, R for randomizing, and RC for mixture of randomizing and clustering. Figure 2 demonstrates the configurations of these three patterns of customers spread. All of the VRPTW instances comprise 100 customer nodes with corresponding (x, y) coordinates, volume of demand, and lower bound and upper bound of required time window.



(a) Randomized scatter (b) Clustered scatter (c) Mixed scatter

Figure 2. Three Geographical Scatter of Customers for VRPTW Instances

We chose three VRPTW instances, C101 from type C, R101 from type R, and RC101 from type RC, as the bases to generate customer's coordinates and demands for MRCVRP instances. Due to the cold logistics, we set three levels of commodities' temperature, i.e., cold (0^{o}C ~ 5^{o}C), refrigerant (-18^{o}C ~ -5^{o}C) and frozen (-30^{o}C below). Moreover, four scenarios were hypothesized for the demands of three-temperature goods as follows.

● Scenario 1: Demands of goods on three temperature levels for all customers are identical.

We established five types of demands for every customer and every temperature level, 10, 20, 30, 40, 50, which adopt the coordinates of customers from C101, R101 or RC101 correspondingly. For example, Instance 1_C-10 means that this instance belongs to scenario 1, the coordinates of customers come from C101, and the demands of goods on three temperature levels for all customers are equal to 10 units. There are total of 15 instances in Scenario 1.

● Scenario 2: Demands of goods for customers are not identical; demands on three temperature levels for some customer are identical.

The coordinates of customers and the demands of goods on every temperature level for customers adopt C101, R101 or RC101 respectively. For example, Instance 2_R-C means that this instance belongs to scenario 2, the coordinates of customers come from R101, the demands of goods for customers come from C101, and the demands of goods on three temperature levels for some customer are identical. There are total of 9 instances in Scenario 2.

● Scenario 3: Demands of goods for customers are not identical; demands on three temperature levels for some customer are different and independent.

The coordinates of customers and the demands of goods on the first temperature level (i.e., cold) for customers adopt C101, R101 or RC101 respectively. To generate independent demands of goods between three temperature levels, we utilize systematic manner to assign three demands of every customer. For example, Instance 3_R-C-11-22 means that this instance belongs to scenario 3, the coordinates of customers come from R101, and the demands of goods for customers on the first temperature level come from C101. In this case, the demand of goods on the second temperature level (i.e., refrigerant) for some customer i is equal to the demand of cold goods for customer i + 11. Similarly, the demand of goods on the third temperature level (i.e., frozen) for customer i is equal to the demand of cold goods for customer i + 22. We design three systematic lags for refrigerant goods (11, 33 and 66) and frozen goods (22, 55 and 88). Therefore, there are total of 27 instances in Scenario 3.

- Scenario 4: Demands of goods for customers are not identical; demands on three temperature levels for some customer are different and dependent.

  Similar to Scenario 3, the coordinates of customers and the demands of goods on the first temperature level for customers adopt C101, R101 or RC101 respectively. In order to generate dependent demands of goods among three temperature levels, we assume that the demands of refrigerant and frozen goods for some customer i are separately equal to reduce and to add the demand of cold goods for customer i by 5 units. For example, Instance 4_R-C means that this instance belongs to scenario 4, the coordinates of customers come from R101, and the demands of cold goods for customers come from C101. Let the demand of cold goods for some customer be 20 units, therefore the demands of refrigerant and frozen goods for this customer are 15 and 25 respectively. There are total of 9 instances in Scenario 4. Generally, the demands in Scenarios 3 and 4 are considered closer to the real-world cases than that in Scenario 1 and 2.

We suppose that the demand of goods on every temperature level for every customer is dividable to load on different refrigerated containers with the same temperature level in the identical vehicle. Additionally, the capacity of vehicles is equal to 400 units and the number of customers is 100 for all sixty instances. The time windows corresponding to every customer originally set in VRPTW are ignored.

5.2 Design of Experiments

This research designs three phases of experiments to analyze the performance and potential of the proposed MRCVRP model and heuristic. The first experiment aims to decide an efficient size of the refrigerated containers, the second experiment tests the effect of the heuristic method proposed in Section 4, and the third experiment compare the MRCVRP with traditional VRP according to their performance on solving instances. Because that the practical cost of trucks and refrigerated containers are unavailable, all experiments consider the quality of solutions at two criteria, the total distance of routes and the total number of vehicles. The details of three-phase experiments explain as follows.

- Phase I: The size of the refrigerated container means the capacity of the container, q. Due that the capacity of a vehicle is 400 units, which is equal to the product of q by p (the maximal number of refrigerated containers that a vehicle can load), we set four combinations of (p, q), i.e., (5, 80), (8, 50), (10, 40) and (20, 20). Four combinations are tested on all sixty instances and solved by six savings algorithms, i.e., sequential SA0 (SSA0), sequential SA1 (SSA1), sequential SA2 (SSA2), parallel SA0 (PSA0), parallel SA1 (PSA1) and parallel SA2 (PSA2). Some combination with the best performance is selected for Phase II.

- Phase II: First, six savings algorithms are tested on all instances. The best savings algorithm is chosen as following initial solution construction module. Then, four interchange-based heuristics, i.e., 2_OPT, (1_0), (1_1) and (2_1), are tested respectively. Finally, various combinations of sequential execution these interchange heuristics are tested.

- Phase III: Instances of Scenario 3 and 4 are used to test the MRCVRP and VRP. In order that VRP can not deliver goods on three temperature levels at one time, we must divide every MRCVRP instance into three VRP instances. Among the three VRP instances, the coordinates of customers are identical, but demands of goods are corresponding to those of different temperature levels. On the other hand, for the consistent purpose, we adopt the SSA0 to construct initial solutions of MRCVRP and VRPs.

5.3 Computational Results

Results of the three-phase experiments are reported and analyzed in this Subsection. As previously mentioned, the total distance of routes (routing distance) and the total number of vehicles (fleet size) are compared respectively.

The results of Phase I testing present that the capacity of refrigerated container greatly influences upon the routing cost and the fleet size. As shown in Table 2, the combination (20, 20) performs well than other combinations. Judging from the averages of the six savings algorithms, the routing distance under the combinations (10, 40) and (20, 20) are smaller than that under combinations (5, 80) and (8, 50) in all four scenarios, and the routing distance under the combination (10, 40) is very close to that under the combination (20, 20) which makes the smallest routing distance, 1530.67. In terms of fleet size, the combination (20, 20) still demands a minimal fleet size of 17.44. It appears that small size of refrigerated container makes full use of the capacity. To simplify the following tests, we only adopt the combination (20, 20) in terms of the refrigerated container's capacity and the maximum number of refrigerated containers packed in each vehicle.

Table 2. Results of Test on the Combination of Parameters p and q

p	q	Average of Scenario 1		Average of Scenario 2		Average of Scenario 3		Average of Scenario 4		Total Average	
		Dist.†	Fleet‡	Dist.	Fleet	Dist.	Fleet	Dist.	Fleet	Dist.	Fleet
5	80	2470.53	36.50	1723.69	21.63	1459.05	16.83	1409.90	15.65	1765.79	22.65
8	50	2252.01	32.83	1525.95	17.61	1382.52	14.75	1415.11	15.59	1643.90	20.20
10	40	1940.88	27.03	1413.98	14.76	1397.55	14.36	1389.28	14.74	1535.42	17.72
20	20	1940.95	27.03	1436.41	14.78	1391.59	13.83	1353.74	14.11	1530.67	17.44

† Dist. denotes the average total distance of routes on six savings algorithms.
‡ Fleet denotes the average total number of vehicles on six savings algorithms.

For the Phase II testing on the six savings algorithms, as shown in Table 3, among the six algorithms, parallel SA0 generates the shortest average routing distance 1405.89, and sequential SA1 (SSA1) renders the lowest average fleet size 17.43. In terms of routing distance, savings algorithms of parallel version obviously perform well than that of sequential version. The SA0 presents the excellent ability to reduce the routing distance, followed by SA2 and SA1. The possible reason is that SA0 focuses on the saving of distance, and the others do not. Oppositely, savings algorithms of sequential version render smaller fleet size than that of parallel version. Even though SSA1 obtains the smallest fleet size, the differences between six algorithms are insignificant. Moreover, the total average of SA0 in fleet size is less than that of SA1. These two modified savings formulas do not seem to work as well as expectation. It may be caused by the less variety of the amounts of demands in testing instances that cannot highlight the effect of saving in capacity. Therefore, we adopt only instances of Scenarios 3 and 4 to the following tests.

Table 3. Results of Test on the Savings Algorithms

Savings Formulas	Sequential (S)		Parallel (P)		Total Average	
	Avg. Dist.†	Avg. Fleet‡	Avg. Dist.	Avg. Fleet	Avg. Dist.	Avg. Fleet
SA0	1504.20	17.30	1405.89	17.52	1455.05	17.41
SA1	1649.16	17.29	1545.53	17.62	1597.35	17.45
SA2	1585.62	17.31	1493.60	17.62	1539.61	17.46
Total Average	1579.66	17.30	1481.68	17.59	1530.67	17.44

† Avg. Dist. denotes the average total distance of routes on sixty instances.
‡ Avg. Fleet denotes the average total number of vehicles on sixty instances.

In order to clearly judge the effect of interchange-base heuristics on improving the initial solution, we select the results of SSA1 to be the initial solutions. Table 4 presents the results of testing on four interchange heuristics, 2_OPT, (1_0), (1_1) and (2_1), where the capacity of refrigerated container is 20 units, the initial solution constructed from sequential SA1, and tested on 36 instances. As shown in Table 4, compared with the initial solutions from SSA1, 2_OPT gains the largest improvement in the average routing distance, followed by (1_1), (1_0) and (2_1) sequentially. Unlike the apparent improvement in routing distance, the average fleet size does not reduce by the four interchange heuristics respectively. The following test focuses on the combinations of these interchange heuristics.

Table 4. Results of Test on the Interchange Heuristics

Interchange Heuristics	Avg. Dist.†	Improvement§	Avg. Fleet‡	Improvement§
Initial Solution: SSA1	1576.58	---	13.81	---
2_OPT Exchange	1462.97	7.21%	13.81	0.00%
(1_0) Interchange	1550.62	1.65%	13.81	0.00%
(1_1) Interchange	1504.98	4.54%	13.81	0.00%
(2_1) Interchange	1555.68	1.33%	13.81	0.00%

† Avg. Dist. denotes the average total distance of routes on thirty-six instances.
‡ Avg. Fleet denotes the average total number of vehicles on thirty-six instances.
§ Improvement denotes the percentage of reduction in routing distance or fleet size.

There are twenty-four combinations of the four interchange are tested on the instances of Scenarios 3 and 4, under the same conditions in the above test. Because that the performances of all combinations are approximate, we only list the best anterior eight combinations in Table 5. As shown in Table 5, the combination (1_1 + 1_0 + 2_OPT +2_1) generates the best results: the average routing distance is 1360.49 and the average fleet size is 13.71, where the percentages of improvement are 13.71% and 0.72% separately. Similar to the previous test, the improvement of routing distance is apparent, but insignificant for that of fleet size.

By the way, the sum of improvements in Table 4 by four interchange heuristics is 14.73% which is close to the improvement 13.71% by combination (1_1 + 1_0 + 2_OPT +2_1). Such a situation reveals that the combined execution of various interchange heuristics is effective and not conflicting.

Table 5. Results of Test on the Combination of Interchange Heuristics

Combinations	Avg. Dist.†	Improvement§	Avg. Fleet‡	Improvement§
Initial Solution: SSA1	1576.58	---	13.81	---
(1_1)+(1_0)+2_OPT+(2_1)	1360.49	13.71%	13.71	0.72%
(1_1)+(1_0)+(2_1)+2_OPT	1360.55	13.70%	13.71	0.72%
(1_1)+2_OPT+(1_0)+(2_1)	1363.14	13.54%	13.72	0.65%
2_OPT+(1_1)+(1_0)+(2_1)	1374.81	12.80%	13.74	0.51%
(1_1)+(2_1)+(1_0)+2_OPT	1356.04	13.99%	13.75	0.43%
(1_1)+(2_1)+2_OPT+(1_0)	1357.47	13.90%	13.75	0.43%
(2_1)+(1_1)+2_OPT+(1_0)	1358.64	13.82%	13.75	0.43%
(2_1)+(1_1)+(1_0)+2_OPT	1358.76	13.82%	13.75	0.43%

† Dist. denotes the average total distance of routes on sixty instances.
‡ Fleet denotes the average total number of vehicles on sixty instances.
§ Improvement denotes the percentage of reduction in routing distance or fleet size.

Table 6. Comparisons of Results between MRCVRP and VRP on Scenario 3

Symbols of Instances	Routing Distance		Fleet Size	
	MRCVRP	3-VRP	MRCVRP	3-VRP
3_C-C-11-22	1328.0	2082.5	14	15
3_C-C-33-55	1209.2	2073.0	15	15
3_C-C-66-88	1270.6	2084.5	14	15
3_C-R-11-22	1375.6	2551.1	14	15
3_C-R-33-55	1364.4	2570.1	15	15
3_C-R-66-88	1318.6	2533.8	14	15
3_C-RC-11-22	1556.5	2826.7	15	15
3_C-RC-33-55	1641.4	2756.5	15	15
3_C-RC-66-88	1527.9	2696.5	14	15
3_R-C-11-22	1337.1	2154.2	14	15
3_R-C-33-55	1232.7	2105.9	14	15
3_R-C-66-88	1256.0	2107.6	14	15
3_R-R-11-22	1310.5	2528.3	14	15
3_R-R-33-55	1310.0	2490.8	14	15
3_R-R-66-88	1256.2	2540.9	14	15
3_R-RC-11-22	1660.9	2750.4	14	15
3_R-RC-33-55	1574.5	2772.3	14	15
3_R-RC-66-88	1558.8	2747.2	14	15
3_RC-C-11-22	1110.3	2043.2	12	12
3_RC-C-33-55	1220.6	1996.9	12	12
3_RC-C-66-88	1182.9	1933.4	12	12
3_RC-R-11-22	1324.5	2474.1	12	12
3_RC-R-33-55	1193.8	2406.2	12	12
3_RC-R-66-88	1296.8	2456.8	12	12
3_RC-RC-11-22	1498.7	2595.0	12	12
3_RC-RC-33-55	1463.5	2640.8	12	12
3_RC-RC-66-88	1493.2	2639.2	12	12
Average	1365.7	2428.1	13.5	14.0
Standard Deviation	150.9	282.9	1.1	1.4
Coefficient of Variance†	11.0%	11.7%	8.1%	10.0%

† Coefficient of variance is the percentage of standard deviation divided by average value.

According to the results of Phases I and II, we propose an efficient and effective implementation of two-stage heuristic for solving the MRCVRP and VRP. In the first stage, we adopt the sequential SA0 (SSA0) to construct the initial solution, then, the combination of (1_1 + 1_0 + 2_OPT +2_1) is utilized in the second stage. The detail results of testing on instances of Scenarios 3 and 4 are respectively reported in Table 6 and Table 7.

Table 7. Comparisons of Results between MRCVRP and VRP on Scenario 4

Symbols of Instances	Distance of Routes		Fleet Size	
	MRCVRP	3-VRP	MRCVRP	3-VRP
4_C-C	1237.0	2177.1	15	15
4_C-R	1230.4	2594.2	15	15
4_C-RC	1476.2	2735.0	15	15
4_R-C	1148.8	2103.5	12	12
4_R-R	1171.7	2450.6	12	12
4_R-RC	1489.6	2635.6	12	12
4_RC-C	1248.0	2187.5	14	15
4_RC-R	1208.0	2594.7	14	14
4_RC-RC	1444.1	2792.9	14	15
Average	1294.8	2474.6	13.7	13.9
Standard Deviation	135.5	258.1	1.3	1.5
Coefficient of Variance†	10.5%	10.4%	9.5%	10.8%

† Coefficient of variance is the percentage of standard deviation divided by average value.

As shown in Table 6, the average routing distance of MRCVRP among twenty-seven instances of Scenario 3 is 1365.7, which is significantly superior to that of VRP (2428.1). Furthermore, the average fleet size of MRCVRP (13.5) is lower than that of VRP (14.0). On the other hand, the standard deviation and coefficient of variance of MRCVRP are smaller than that of VRP. Hence, the MRCVRP performs more steadily than the VRP does.

Additionally, same results can be experienced in Table 7. The average routing distance of MRCVRP among nine instances of Scenario 4 (1294.8) is significantly superior to that of VRP (2474.6), as well as the average fleet size of MRCVRP (13.7) is lower than that of VRP (13.9). Once more, the standard deviation and coefficient of variance of MRCVRP are less than that of VRP.

Judging from the computational results in Phase III, we think that the MRCVRP model has explicit potentiality to lift the performance of cold logistics and distribution. Not only apparently diminish the routing distance, but the MRCVRP also enables to lower the capital investment on refrigerated transport equipments if that the cost of multi-temperature refrigerated containers is less than that of chill trucks. Generally speaking, the chill truck is of much higher purchase cost and maintenance cost than general vehicles. In sum, MRCVRP is preferable to the multi-temperature fresh-keeping delivery service.

6. CONCLUSIONS AND SUGGESTIONS

6.1 Findings and Conclusions

Multi-temperature fresh-keeping delivery service is gradually popularized in the convenience stores, supermarkets and cold food markets. With the invention of multi-temperature refrigerated container and transport system, it offers a bran-new technology and business solution in cold logistics practice. This article proposes a MRCVRP (Multi-temperature Refrigerated Container Vehicle Routing Problem) model which enables to be applied in multi-temperature fresh-keeping delivery service and to deliver multi-temperature goods in general trucks.

The main contributions of the study are to put forward the mathematical programming formulation of MRCVRP, and design a two-stage heuristic method that combines the modified savings algorithm and four interchange-based heuristics. Moreover, a set of sixty instances modified from Solomon's VRPTW benchmark instances is adopted to verify the feasibility of the MRCVRP model by three phases of experiments.

According to the computational results, we found that: (1) sequential SA1 obtains the smallest average fleet size and parallel SA0 renders the shortest average routing distance; (2) combination of four interchange heuristics is effective in lowering down the routing distance; and (3) among thirty-six instances, the MRCVRP performance apparently well than the traditional VRP. Therefore, we conclude that MRCVRP presents high potentiality to be applied on the multi-temperature fresh-keeping delivery service in the distribution operation of the cold logistics companies.

6.2 Further Topics and Suggestions

The study only proposes the basic mathematical formulation and a heuristic algorithm for MRCVRP, and proves its benefit by means of experimental tests. There are many subjects still to be discussed. The following issues shall be considered in future researches on MRCVRP:

1. The manners to construct the initial solution are only available with original and modified savings algorithms, which should have been enhanced by proposing more powerful savings formulas. Furthermore, other methods, such as the nearest neighbor algorithm and the insertion-based algorithms, could be considered.

2. This study designs a simple heuristic method applicable to solve the MRCVRP, yet there is something could be improved. For example, introduction of some meta-heuristics, such as the tabu search, ant system and threshold accepting, is possible to promote the performance of problem-solving.

3. This study assumes that the capacity of vehicle and refrigerated container are fixed. Hence, vehicles or refrigerated containers of different sizes can be simultaneously considered in the future.

4. Further consideration of real situation, such as the time-window constraint on serving customers should be emphasized and involved into the MRCVRP model.

5. It is important to collect the actual cost and operating data from some cold logistics companies, such as cold distribution center, and home delivery, which have adopted the multi-temperature refrigerated container to deliver goods. Usage of these data, we can identify the real performance of MRCVRP and maybe reduce the transportation cost of the cold logistics companies.

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