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Optimal delivery cycles for joint distribution of multi-temperature food

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ABSTRACT

The need for fresh, refrigerated, and frozen food has been continuously growing due to high demand for healthy and convenient diets in urban fast-paced daily living. Correspondingly, the market for low temperature logistics is expanding due to demand for low-temperature food, and the process of delivering food requiring storage and shipping in containers with different temperature ranges has become an important issue for carriers. This study analyzes optimal delivery cycles for jointly delivering multi-temperature food using Traditional Multi-Vehicle Distribution and Multi-Temperature Joint Distribution systems. We formulate mathematical models for the systems considering a variety of time-dependent demands and time-windows for delivering different temperature range foods to various customers. The models provide effective tools that determine delivery cycles and dispatching lists for carriers. The results show both carriers and shippers benefit from jointly delivering different temperature range foods using a single vehicle to ensure the freshness of the food.

1. Introduction

The need for fresh, refrigerated, and frozen food has continuously grown in recent years due to high demand for healthy and convenient diets in urban fast-paced daily living. According to Global Cold Chain Alliance (2008), demand for temperature-controlled food is increasing in many markets across the globe; thus, the market for low-temperature logistics is expanding. Hsu and Liu (2011) defined multi-temperature logistics as encompassing all processes involving the movement and storage of cargos in an efficient and cost-saving manner, where optimal temperature control is necessary to maintain the cargos' original value and quality. However, time-dependent demand patterns may vary widely for different temperature range foods. For example, demand for deep frozen food, like tuna, usually occurs in the early morning, but some fresh food served during lunchtime is needed just before noon; therefore, the optimal delivery cycle for each temperature range may be different. This study aims to analyze optimal delivery cycles for jointly delivering multi-temperature food using both the Traditional Multi-Vehicle Distribution (TMVD) and Multi-Temperature Joint Distribution (MTJD) systems. We formulate a mathematical model for each system considering a variety of time-dependent demands and time-windows for delivering different temperature range foods to various customers.

TMVD uses one type of refrigerated vehicle to distribute cargos in a single temperature range around a set-point, such as vehicles with temperatures set at −20 °C, 0 °C or +12 °C. Refrigerated vehicles maintain the required temperature using a mechanical compression refrigeration unit driven by an engine. This temperature control system is usually affected by the frequency and duration of vehicle door opening, thus it cannot be tuned precisely. However, in multi-compartment vehicles, the refrigerated space is subdivided into a number of compartments with individual temperature set-points to provide flexibility for business operations (Tassou, De-Lille, & Ge, 2009). Compared with TMVD, the MTJD technique can simultaneously transport goods at two or more temperature ranges in a single vehicle. Kuo and Chen (2010) pointed out the logistical costs of handling frequent deliveries in small lots using less than truckload (LTL) transportation can be significantly reduced using the MTJD model, while maintaining customer satisfaction. In this study, the MTJD system uses replaceable cold accumulators inside insulated boxes and cabinets to maintain precise temperatures and then uses these cold boxes and cabinets to carry different temperature range foods in regular vehicles for shipping. Therefore, in a regular vehicle, the proportion of space used by each temperature range food can be allocated based on dynamic demand during each period. Since temperature control relies on cold boxes and cabinets, the technique can avoid food deterioration resulting from bacteria due to repeated opening

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of the vehicle's doors. Moreover, with MTJD, a carrier can unload foods of all temperature ranges at a single customer's location at the same time; thus, it not only saves carrier costs but also reduces handling time and enhances the level of customer service.

For research regarding transportation networks for perishable goods, Zhang, Habenicht, and Spieß (2003) presented a tabu search algorithm to optimize the structure of cold chains. Hsu, Hung, and Li (2007) studied a vehicle routing problem with time-windows for delivering perishable food. In addition to distribution networks, many studies have focused on the phenomenon of quality and shelf life decay over time (e.g. Bogataj, Bogataj, & Vodopivec, 2005; Likar & Jevsnik, 2006). There are numerous related studies in the chemical and process engineering field (e.g. Borghi, Guirardello, & Filho, 2009). Food distribution strategies are currently tending toward the use of shipments containing a variety of food types in small amounts and at varying temperatures, but there are few studies that provide a rationale for this shift. In response, this study constructs a mathematical programming model to optimize delivery cycles for multi-temperature food considering time-dependent demands and joint distribution. Through the proposed model, carriers can determine what temperature range foods should be loaded on the vehicles during different periods to minimize costs.

The reminder of this paper is organized as follows. Sections 2 and 3 describe the formulation of the MTJD and TMVD systems, respectively. An algorithm to solve the models in this study is developed in Section 4, and Section 5 presents a numerical example to illustrate the feasibility and results of the models. Finally, conclusions are summarized in Section 6.

2. Model formulation for the MTJD system

This section examines how time-dependent demand for different temperature-range foods influences operation costs for carriers. The delivery cycle (or frequency) for each temperature range food is an importation issue for a carrier because these decisions directly influence operating costs of the carrier and the quality of service provided to shippers. Carriers generally enhance their transportation offerings by providing high frequency (low cycle) service to reduce transportation time. On the other hand, inventory costs related to cargos in a distribution center waiting to be shipped also depend on the delivery cycle, and are borne by both carriers and shippers. Therefore, in this study, transportation and inventory costs are regarded as two of the major factors affecting delivery service decisions. Furthermore, this study extends the cost formulation to include energy costs due to using cold boxes and cabinets for storing perishable foods, and penalty cost for violating delivery time windows. Therefore, the optimal delivery cycle for each temperature range food and shipping list for each period are generated by minimizing the total cost, which includes transportation, inventory, penalty, and energy costs. In this study, carriers are assumed to provide fixed delivery cycles and have their own distribution centers, vehicle fleets, and temperature control equipment for delivering food to their customers. Customers in this study are defined as general retailers and are assumed to know the carrier's service level (i.e., delivery cycle for each temperature range) when choosing a carrier. This study explores how carriers decide on a delivery list for each period.

In this study, ordered food will be shipped in the delivery cycle that is closest to the demand time for the corresponding temperature range. Thus, shippers can forecast before deciding whether the fixed cycles will ensure the food will be delivered in time. In such situations, the costs associated with routing distance have no direct influence on determining delivery cycles. Therefore, the issues related to the vehicle routing problem, which are usually solved when the delivery list is known, are not taken into account in this study. Let D_r be the delivery cycle of temperature range r food. Thus, if food i needs to be stored in temperature range r, the time food i, needed by retailer j at period t, leaves the distribution center, y_{sijt}, can be expressed as nD_r, where n is a natural number because the time when food i leaves the distribution center must be a multiple of D_r. The value of n for each order is discussed in Section 2.4. Moreover, this study formulates a mathematical programming model for determining the optimal delivery cycle for each temperature range considering dynamic demand and different components of total operation cost; we assume the carriers are seeking to minimize total cost.

2.1. Transportation and energy costs

In this study, transportation costs involve both a fixed cost for dispatching vehicles and a cost for loading/unloading cold boxes and cabinets. This study assumes that carriers have sufficient vehicles to carry all ordered food at each period. The fixed cost for dispatching regular vehicles can be expressed as $\sum_t k_t f$, where k_t is the number of vehicles dispatched at period t, and f is the fixed cost for dispatching a regular vehicle.

The loading/unloading cost depends on the quantity transported per shipment. We denote $N_{rt\tau}$ and $N_{rt\Gamma}$ as the numbers of temperature range r cold boxes and cabinets used at period t, and δ_τ and δ_Γ as the loading/unloading costs per unit cold box and cabinet, respectively. Furthermore, the total loading/unloading cost, C_L, can be formulated as

$$C_{\mathrm{L}} = \sum_r \sum_t \delta_\tau N_{rt\tau} + \delta_\Gamma N_{rt\Gamma} \quad (1)$$

This study focuses on the tradeoff between using cold boxes and cabinets, the capacities of which are 90 L and 936 L, respectively. However, the numbers of cold boxes and cabinets influence not only the loading/unloading cost but also the energy cost of the MTJD system. The energy cost arises from the energy consumption of the cold accumulators inside the cold boxes and cabinets. Therefore, the energy cost depends on the numbers of cold boxes and cabinets used. Let ϕ_r and Φ_r denote the energy cost per unit box and cabinet, respectively, for temperature range r. Then the total energy cost, C_{E}, can be expressed as

$$C_{\mathrm{E}} = \sum_r \sum_t (\phi_r N_{rt\tau} + \Phi_r N_{rt\Gamma}) \quad (2)$$

For this study, a survey was conducted to identify factors affecting costs for using cold boxes and cabinets. The data provided evidence that the loading/unloading cost and energy cost per unit capacity for one cold cabinet are less than those for one box. Therefore, we assume all food is packed into cold cabinets, but if the carrier uses a cold cabinet that is not full, then consideration should be given as to whether the food should be moved to cold boxes. That is, the study derives the critical volume that determines whether to use several boxes to replace a cold cabinet to yield the lowest loading/unloading and energy costs. Since the cost for using a box and a cabinet can be formulated as $(\delta_\tau + \phi_r)$ and $(\delta_\Gamma + \Phi_r)$, respectively, the loading/unloading and energy costs of $[(\delta_\Gamma + \Phi_r)/(\delta_\tau + \phi_r)]$ units of cold boxes for temperature range r is equal to that of one cold cabinet for the same temperature range. Let V_τ denote the capacity of one unit cold box. Therefore, the critical volume for using cold boxes can be derived as $V_\tau[(\delta_\Gamma + \Phi_r)/(\delta_\tau + \phi_r)]$, which is the total capacity of $[(\delta_\Gamma + \Phi_r)/(\delta_\tau + \phi_r)]$ units of boxes. If the amount of food in an unfilled cabinet is less than the critical volume, the food should be moved to cold boxes; otherwise, that food should be kept in the cold cabinet. We assume approximately full capacity utilization for all boxes and cabinets. Furthermore, the number of boxes and cabinets used at period t for temperature range r, $N_{rt\tau}$ and $N_{rt\Gamma}$, can be expressed as

$$N_{rt\tau} = \begin{cases} 0, & \text{if } \left(\sum_{\gamma_i=r}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i\right)\bmod V_\tau > \left(\dfrac{\delta_\Gamma+\Phi_r}{\delta_r+\phi_r}\right) \\ \left\lceil \dfrac{\left(\sum_{\gamma_i=r}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i\right)\bmod V_\tau}{V_\tau} \right\rceil, & \text{if } \left(\sum_{\gamma_i=r}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i\right)\bmod V_\tau \le \left(\dfrac{\delta_\Gamma+\Phi_r}{\delta_r+\phi_r}\right) \end{cases} \quad (3)$$

and

$$N_{rt\Gamma} = \begin{cases} \left\lfloor \dfrac{\sum_{\gamma_i=r}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i}{V_\tau} \right\rfloor, & \text{if } \left(\sum_{\gamma_i=r}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i\right)\bmod V_\tau > \left(\dfrac{\delta_\Gamma+\Phi_r}{\delta_r+\phi_r}\right) \\ \left\lceil \dfrac{\sum_{\gamma_i=r}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i}{V_\tau} \right\rceil, & \text{if } \left(\sum_{\gamma_i=r}^{0}\sum_{j}\sum_{y_{sijt}=t} Q_{ijt}V_i\right)\bmod V_\tau \le \left(\dfrac{\delta_\Gamma+\Phi_r}{\delta_r+\phi_r}\right) \end{cases} \quad (4)$$

respectively, where Q_{ijt} is the amount of food i needed by retailer j at period t; γ_i denotes the temperature range in which food i needs to be stored. Symbol V_Γ denotes the capacity of one unit cold cabinet. Consequently, the transportation cost of the MTJD system during the entire study period, C_T, can be expressed as

$$C_{\mathrm{T}} = \sum_t k_t f + \sum_r \sum_t (\delta_\tau N_{rt\tau} + \delta_\Gamma N_{rt\Gamma}) \quad (5)$$

2.2. Inventory cost

In this study, inventory cost is determined by the difference between the time food arrives at the distribution center and leaves the distribution center. Furthermore, the total inventory cost of the MTJD system, C_{I}, can be presented as

$$C_{\mathrm{I}} = \sum_i \sum_j \sum_t Q_{ijt}\beta_i\left(y_{sijt} - y_{fijt}\right) \quad (6)$$

where y_{fijt} and y_{sijt} are the times when food i, needed by retailer j at period t, arrives at and leaves the distribution center, respectively. Symbol β_i denotes the inventory cost per unit of time per item of food i stored in the distribution center, which involves the cost for storage and temperature control.

2.3. Penalty cost

This study assumes retailers accept soft delivery time-windows. When a vehicle arrives early, or within an acceptable period of delay, the food can be still delivered with a penalty cost. Let $\lfloor u_{ijt}, s_{ijt} \rfloor$ be the soft time-window for food i, needed by retailer j at period t. Symbols U_{ijt} and S_{ijt} denote the earliest acceptable time for early arrival and the latest acceptable time for late arrival, respectively, of food i, needed by retailer j at period t, and $U_{ijt} \le u_{ijt}$, $S_{ijt} \ge s_{ijt}$. The relationship between penalty cost and arrival time can be seen in Fig. 1, which shows the acceptable periods for early arrival and delay for food i needed by retailer j at period t are $\lfloor U_{ijt}, u_{ijt})$ and $(s_{ijt}, S_{ijt}\rfloor$, respectively. There are different penalties for each range. When arrival time is beyond $\lfloor U_{ijt}, S_{ijt} \rfloor$, the customer may refuse to receive the food and the carrier should pay the customer a penalty, c_i, for each item of food i. Hence, the penalty cost due to violating the earliest and latest acceptable times in the time-window for food i ordered by retailer j at period t can be expressed as $Q_{ijt}c_i$.

According to Hsu et al. (2007), the penalty cost, due to violating the upper bounds of the soft time-window, $\lfloor u_{ijt}, s_{ijt} \rfloor$, specified by retailer j who needs food i at period t, can be formulated as $Q_{ijt}H_i d_i (D_r n + \rho_j - s_{ijt})^{v}{}_i$, where ρ_j is the expected travel time from the distribution center to retailer j's location, and H_i is the value of unit item of food i. Symbols d_{ij} and v_i are parameters; $d_i \le 1$ and $v_i \ge 1$.

Furthermore, the penalty cost for food i needed by retailer j at period t, $C_{\mathrm{P1}}(Q_{ijt})$, can be formulated as

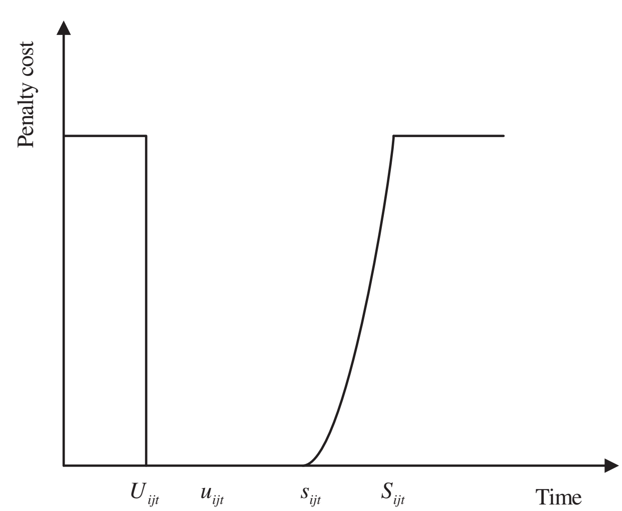

Fig. 1. The relationship between arrival time, time-windows, and penalty cost.

$$C_{P1}(Q_{ijt}) = \begin{cases} Q_{ijt}c_i, & \text{if } nD_r+\rho_j<U_{ijt} \\ 0, & \text{if } U_{ijt}\le nD_r+\rho_j<u_{ijt} \\ 0, & \text{if } u_{ijt}\le nD_r+\rho_j\le s_{ijt} \\ Q_{ijt}H_id_i(nD_r+t_j-s_{ijt})^{v_i}, & \text{if } s_{ijt}\le nD_r+\rho_j\le S_{ijt} \\ Q_{ijt}c_i, & \text{if } nD_r+\rho_j\ge S_{ijt} \end{cases} \quad (7)$$

and the total penalty cost for the MTJD system, C_P, can be calculated as $\sum_i\sum_j\sum_t C_{P1}(Q_{ijt})$.

2.4. Formulation of the optimal problem

As regards a shipment dispatched at each period, this study assumes the carrier dispatches orders whose demand time falls in $[(nD_r-D_r/2),(nD_r+D_r/2))$ at nD_r. Let $M_{r,n}$ denote the time interval during which the carrier accumulates temperature range r food to dispatch at nD_r. This study divides operation duration into m periods. Furthermore, $M_{r,n}$ for even and odd n can be formulated as follows.

If cycle D_r is an even number i.e., $D_r=2N$, $N\in[1,2,\ldots m/2]$,

$$M_{r,n} = \begin{Bmatrix} \left[D_rn-\left(\frac{D_r}{2}-1\right),\ D_rn+\frac{D_r}{2}\right] & \text{if } n=2,3,\ldots,\frac{m}{D_r}-1 \\ \left[1,\ D_rn+\frac{D_r}{2}\right] & \text{if } n=1 \\ \left[D_rn-\left(\frac{D_r}{2}-1\right),\ 24\right] & \text{if } n=\frac{m}{D_r} \end{Bmatrix} \quad (8)$$

If cycle D_r is an odd number, i.e., $D_r=2N-1$, $N\in[1,2,\ldots m/2]$,

$$M_{r,n} = \begin{Bmatrix} \left[D_rn-\left(\frac{D_r-1}{2}\right),\ D_rn+\left(\frac{D_r-1}{2}\right)\right] & \text{if } n=2,3,\ldots,\frac{m}{D_r}-1 \\ \left[1,\ D_rn+\left(\frac{D_r-1}{2}\right)\right] & \text{if } n=1 \\ \left[D_rn-\left(\frac{D_r-1}{2}\right),\ 24\right] & \text{if } n=\frac{m}{D_r} \end{Bmatrix} \quad (9)$$

Furthermore, the time that food i needed by retailer j at period t leaves the distribution center, y_{sijt}, can be determined as

$$y_{sijt} = nD_r \quad (10)$$

where n is a positive integer such that $(nD_r-D_r/2)\le t<(nD_r+D_r/2)$.

To avoid increasing penalty and other costs for orders that cannot be delivered between the earliest and latest acceptable times, this study assumes the carriers would not dispatch food that retailers would refuse to receive. Let ε_{ijt} be a binary variable, if the penalty for food i, needed by retailer j at period t, is $Q_{ijt}c_i$, $\varepsilon_{ijt}=0$; otherwise, $\varepsilon_{ijt}=1$.

Furthermore, a nonlinear programming problem can be formulated here for determining the optimal delivery cycle for each temperature range, $D_r, \forall r$, for the MTJD system, by minimizing the total operation cost subject to the delivery time-window for each order. From the above discussion, the nonlinear programming problem for minimizing cost throughout the study period is as follows.

$$\min_{D_r,\forall r} \quad C_T+C_E+C_I+C_P \quad (11\text{-a})$$

s.t.

$$C_T = \sum_t k_tf+\sum_r\sum_t(\delta_\tau N_{rt\tau}+\delta_\Gamma N_{rt\Gamma}) \quad (11\text{-b})$$

$$C_E = \sum_r\sum_t(\phi_rN_{rt\tau}+\Phi_rN_{rt\Gamma}) \quad (11\text{-c})$$

$$C_I = \sum_i\sum_j\sum_t Q_{ijt}\beta_i\left(y_{sijt}-y_{fijt}\right) \quad (11\text{-d})$$

$$C_P = \sum_i\sum_j\sum_t C_{P1}(Q_{ijt}) \quad (11\text{-e})$$

$$C_{P1}(Q_{ijt}) = \begin{cases} Q_{ijt}c_i, & nD_r+\rho_j<U_{ijt} \\ 0, & U_{ijt}\le nD_r+\rho_j<u_{ijt} \\ 0, & u_{ijt}\le nD_r+\rho_j\le s_{ijt} \\ Q_{ijt}P_id_i\left(nD_r+\rho_j-s_{ijt}\right)^{v_i}, & s_{ijt}\le nD_r+\rho_j\le S_{ijt} \\ Q_{ijt}c_i, & nD_r+\rho_j\ge S_{ijt} \end{cases} \quad (11\text{-f})$$

$$y_{sijt} = nD_r \quad \ni(nD_r-D_r/2)\le t<(nD_r+D_r/2) \quad \forall i,j,t \quad n\in N^+ \quad (11\text{-g})$$

$$N_{rt\tau} = \begin{cases} 0, & \text{if } \left(\sum_{\gamma_i=r}\sum_j\sum_{y_{sijt}=t}Q_{ijt}V_i\right)\bmod V_\tau > \left(\frac{\delta_\Gamma+\Phi_r}{\delta_r+\phi_r}\right) \\ \left\lceil\frac{\left(\sum_{\gamma_i=r}\sum_j\sum_{y_{sijt}=t}Q_{ijt}V_i\right)\bmod V_\Gamma}{V_\tau}\right\rceil, & \text{if } \left(\sum_{\gamma_i=r}\sum_j\sum_{y_{sijt}=t}Q_{ijt}V_i\right)\bmod V_\tau \le \left(\frac{\delta_\Gamma+\Phi_r}{\delta_r+\phi_r}\right) \end{cases} \quad (11\text{-h})$$

$$N_{rt\Gamma} = \begin{cases} \left\lceil \dfrac{\sum\limits_{\gamma_i=r} \sum\limits_{j} \sum\limits_{y_{sijt}=t} Q_{ijt} V_i}{V_\Gamma}, \right\rceil & \text{if} \quad \left(\sum\limits_{\gamma_i=r} \sum\limits_{j} \sum\limits_{y_{sijt}=t} Q_{ijt} V_i \right) \text{mod} V_\tau > \left(\dfrac{\delta_\Gamma + \Phi_r}{\delta_r + \phi_r} \right) \\ \left\lfloor \dfrac{\sum\limits_{\gamma_i=r} \sum\limits_{j} \sum\limits_{y_{sijt}=t} Q_{ijt} V_i}{V_\Gamma}, \right\rfloor & \text{if} \quad \left(\sum\limits_{\gamma_i=r}^{0} \sum\limits_{j} \sum\limits_{y_{sijt}=t} Q_{ijt} V_i \right) \text{mod} V_\tau \le \left(\dfrac{\delta_\Gamma + \Phi_r}{\delta_r + \phi_r} \right) \end{cases} \tag{11-i}$$

Eq. (11-a) represents the objective function that minimizes costs throughout the study period. Eqs. (11-b)–Eq. (11-d) define the transportation, energy, and inventory costs as Eq. (5), Eq. (2), and Eq. (6), respectively. Eq. (11-e) defines the penalty cost. Eq. (11-f) represents the relationship between penalty cost and delivery time. Eq. (11-g) presents the relationship between optimal delivery cycles and the time food leaves the distribution center for each order. Finally, Eq. (11-h) and Eq. (11-i) express the formulation of the numbers of cold boxes and cabinets used, respectively, during each period.

3. Model formulation for the TMVD system

In order to understand the advantages of the MTJD system, this study constructs a mathematical programming model for determining the optimal delivery cycle for the TMVD system. Thus, the cost structures and service levels of the two different systems can be compared. As discussed in Section 1, the differences between the MTJD and TMVD systems involve facility flexibility, cost for purchasing and using vehicles, and energy resources for temperature control. In practice, the temperature ranges for refrigerated vehicles can be modulated by vehicle freezer systems. However, the cost for changing the temperature range by replacing freezer systems is very large; therefore, the temperature range for refrigerated vehicles is usually fixed. To accurately compare the operation costs of the MTJD and TMVD systems, this study assumes the temperature range divisions for the two systems are the same. Therefore, the mathematical programming model for determining optimal delivery cycles for the TMVD system is similar to the MTJD system, except for some equations. This section illustrates the differences in model formulation between the MTJD and TMVD systems.

Let N_t^r be the number of normal containers used for temperature range r food at period t without the function of temperature control. In practice, the normal containers are made from thick paper or plastics, but this study assumes they are made of plastic and are of identical size. Similar to the MTJD system, the number of containers used at period t, N_t^r, can be calculated as

$$N_t^r = \left\lceil \frac{\sum\limits_{\gamma_i==r} \sum\limits_{j} \sum\limits_{y_{sijt}=t} Q_{ijt} V_i}{V_\mathrm{N}} \right\rceil \tag{12}$$

where V_N is capacity of one normal container; δ denotes the loading/unloading cost per one unit normal container. Furthermore, the transportation cost of the TMVD system, C'_T, can be expressed as

$$C'_\mathrm{T} = \sum_t \sum_r k_t^r f^r + \sum_t \sum_r \delta N_t^r \tag{13}$$

where k_t^r is the number of temperature range r vehicles dispatched at period t, and f^r is the fixed cost for dispatching a temperature range r vehicle.

Regarding energy cost, let F^r be the energy cost for using a temperature range r vehicle; furthermore, the energy cost of the TMVD system can be expressed as $\sum\limits_r \sum\limits_t k_t^r F^r$. However, in practice, there exists a loss of energy due to opening the cargo hold because the temperatures inside and outside refrigerated vehicles are different. Such loss of energy depends on the amount of time the cargo hold is open, which is related to unloading time at a customer's location. Let t_N denote the time duration to unload a container from the vehicle, and α_r be the cost for lost energy per unit of time for temperature range r vehicle. Thus, the cost of energy loss due to opening the cargo hold in the TMVD system can be calculated as $\sum\limits_r \sum\limits_t \alpha_r N_r^t t_N$. Furthermore, the total energy cost of the TMVD system, C'_E, can be formulated as

$$C'_\mathrm{E} = \sum_r \sum_t k_t^r F^r + \sum_r \sum_t N_r^t t_N \alpha_r \tag{14}$$

Hsu et al. (2007) formulated a loss of inventory cost using a probability density function. Let $G(Q_{ijt})$ be the probability that Q_{ijt} items of food i, ordered by retailer j at period t, perished due to opening the cargo hold per unit of time. The greater the difference in temperature inside and outside the vehicle, the higher the probability that food perished; that is, the probability that food perished at noon is higher than at other times during the day. The loss of inventory for the TMVD system can be expressed as $\sum\limits_i \sum\limits_j \sum\limits_t H_i Q_{ijt} G(Q_{ijt}) N_r^t t_\mathrm{N}$. Furthermore, the total inventory cost of the TMVD system, C'_I, can be expressed as

$$\begin{aligned} C'_\mathrm{I} = & \sum_i \sum_j \sum_t Q_{ijt} \beta_i \left(nD_r - y_{fijt} \right) \\ & + \sum_i \sum_j \sum_t H_i Q_{ijt} G(Q_{ijt}) N_r^t t_\mathrm{N} \end{aligned} \tag{15}$$

The programming model for determining the optimal delivery cycle for different temperature ranges by minimizing cost through the study period for the TMVD system can be formulated in the same manner as for the MTJD system. However, the transportation, energy, and inventory cost functions would be replaced by Eqs. (13)–(15), respectively. In addition, the formulation related to cold boxes and cabinets would be replaced by Eq. (12). This study further compares the objective value between the MTJD and TMVD systems by a numerical example in Section 5.

4. Algorithm

We assume delivery cycles for all temperature ranges are natural numbers, in terms of the unit of time being studied; therefore, a general integer programming model is formulated since all decision variables are positive integers. The solutions for the proposed models include optimal delivery cycles for each temperature range.

This study divides operation duration into m periods. For a carrier transporting ℓ different ranges food, there are ℓ integer decision variables and m^{ℓ} feasible solution combinations. Time for solving the proposed models exponentially increases with the number of variables. Furthermore, if we assume the delivery cycle must be a factor number of m (i.e., the domain of decision variables is a combination of factor numbers of m), for ℓ temperature ranges, there are ℓ explicit constraints, and the number of feasible solutions decreases. On the other hand, many variables in the cost functions depend on the decision variables. For example, the numbers of cold boxes and cabinets at each period depend on delivery cycle combinations. Therefore, for a problem with m periods and ℓ ranges, there are $m\ell$ element constraints for cold boxes and cabinets, respectively. In addition, the penalty cost of each shipment also depends on delivery cycles, as shown in Eq. (7). For each shipment, there is an element constraint for penalty calculation. According to Hillier and Lieberman (2009: chap. 12), the process of applying constraint programming to integer programming problems involves efficiently finding feasible solutions that satisfy all constraints and searching for the optimal solution among these solutions. The methods include enumerating solutions and adding a constraint that tightly bounds the objective function to values that are very near to what is anticipated for the optimal solution. In sum, due to the large numbers of constraints and feasible solutions, it is difficult and time-consuming to find an optimal solution; thus approximate methods are required. The most commonly used approaches are a genetic algorithm (GA) and simulated annealing (SA). However, adapting GA tends to be computationally expensive (Mishra, Dutta, & Ghosh, 2003), and the crossover rule is not suitable for the proposed models because they are not sequence problems, and the delivery cycles for each temperature do not influence each other due to the assumption of sufficient vehicles and shipping equipment. As for SA, it has been extensively used in solving many difficult optimization problems. The major advantage of the SA algorithm is the ability to avoid becoming trapped in the local optimal. Therefore, this study adopted the SA algorithm to solve the optimal solution for each system. In this section, we first develop an approach to generate an initial solution, and then use the SA algorithm to develop a heuristic to improve the initial solution. The heuristic for improving the solution is described as follows.

4.1. Initial solution (INIT)

Since local improvement methods must start with a feasible solution, this study develops a heuristic to generate initial solutions. Based on the characteristics of transportation with economies of scale, the average delivery cost per unit item can be reduced if more food is assigned to a vehicle with a larger capacity. However, for perishable food, service level (i.e., delivery time) influences the shipment and revenue of a carrier more than other categories of cargos because such food usually decays with time. This study considers the time-dependence of food demand and vehicle capacity to design a procedure to generate initial solutions that minimize late delivery and ensure the greatest capacity of cold boxes or cabinets that can be used. The procedure is described as follows.

Step 1. Calculate the average duration between two shipping demands, X_r for each temperature range (i.e., $r = 1\sim\ell$).

Step 2. Calculate the average shipping demand during X_r, ϖ_r^X, that is, $\varpi_r^X = \sum_i \sum_j \sum_t Q_{ijt} V_i/(m/X_r), r = 1\sim\ell$, where m is the number of periods. If $\varpi_r^X > V_\tau$, the initial delivery cycle of temperature range r, is the factor number of m, which is both closer and larger than X_r. If $\varpi_r^X \le V_\tau$, find the smallest natural number n' such that $n'X_r > V_\tau$, and let the initial delivery cycle of temperature range r be the factor number of m, which is both closer and larger than $n'X_r$.

4.2. Simulated annealing (SA)

The values of the SA algorithm parameters include (1) the initial temperature $Z_0 = 99$; (2) the decreasing ratio of temperature is 0.95, and the stop temperature is 0.1; and (3) the number of moves at each temperature is 50.

Referring to Heragu and Alfa (1992) and Yan and Luo (1999), the SA algorithm can be described as follows.

Step 0 Employ INIT to find an initial feasible solution, A, and calculate its objective function, $z(A)$.

Step 1. At temperature Z_x, implement the Metropolis algorithm (Metropolis, Rosenbluth, Rosenbluth, & Teller, 1953):

1.1. Randomly choose a temperature range r and randomly generate a variable $\pi\sim U(0,1)$; if $y \ge 0.5$, $T_r = T_r + 1$; otherwise, $D_r = D_r - 1$. Let the altered solution be adjacent solution, A'. Calculate the objective value $z(A')$ for adjacent solution S'.

1.2 Determine whether the new solution is accepted.

1.2.1 Calculate the difference between the objective function of A and A', $\Delta = z(A') - z(A)$.

1.2.2 If $\Delta < 0$, then $A = A'$; else randomly generate a variable $\pi_1 \sim U(0,1)$. If $\exp(-\Delta/Z_x) \ge \pi_1$, then $A = A'$; else go to Step 1.

1.2.3 If the stop criteria of the Metropolis algorithm are satisfied, then go to Step 2, else go to Step 1.

Step 2. If the stop criteria of the SA algorithm are satisfied, then go to Step 3; else let $x = x + 1$ and $Z_{x+1} = 0.95Z_x$, and go to Step 1.

Step 3. Output the optimal delivery cycle for each temperature range food, $A^* = (D_1,D_2,D_3,D_4,D_5)$.

Table 1
Initial values of food demand.

Temperature range r	Food code i	Food	P_i (NT$)	V_i (L)	β_i	c_i (NT$)	μ_i (h)	v_i
Range 1 : −30 °C	1	Tuna	2000	25	1	3000	20	2
Range 2 : −30 °C to −18 °C	2	Ice cream	200	0.08	0.8	300	24	1.2
	3	Ice cube	150	2.5	2	225	12	1.1
	4	Frozen dumpling	100	2	1.5	150	24	1.3
Range 3 : 0 °C to 7 °C	5	Milk	120	0.75	1	180	12	1.2
	6	Juice	20	0.4	0.8	30	24	1.2
Range 4 : 18 °C	7	Cookie	30	2	0.1	45	24	1.5
	8	Medicine	80	0.05	0.2	120	12	1.05
Range 5 : 40 °C	9	Lunchbox	60	0.75	0.4	90	12	1.5
	10	Hot meal	300	10	0.5	450	6	1.5

Table 2
Expected travel time from distribution center to retailers.

Retailers	Expected travel time (min)	Retailers	Expected travel time (min)
1	5	6	30
2	10	7	35
3	15	8	40
4	20	9	45
5	25	10	50

5. Numerical example

This section presents an application of the proposed models, using a numerical example. This study generates a random extraction of the characteristics of 10 customers, which include locations, demand times, time-window constraints and items, and amount of food demand in different temperature ranges. Customers' time-windows are generated between 0:00 and 24:00. For simplicity, this study assumes one operating day, namely 24 h, as the study period, with the unit of time for the study being 1-h intervals. This study uses five temperature ranges, with the food list for each range shown in Table 1, while Table 2 shows the expected travel time to each customer. Table 3 lists the parameters related to operation of the distribution center. Fig. 2 illustrates time-dependent demand for each temperature range food during the entire study period. The demand time for each order is defined as the midterm of its time-window. Using the algorithm presented in Section 4, the proposed models in Sections 2 and 3 can be implemented and the optimal delivery cycle for each temperature range can be determined for the MTJD and TMVD systems, respectively.

Table 4 lists the results and optimal objective function values for MTJD and TMVD system, respectively. The optimal delivery cycles for the MTJD system for five temperature ranges (TRs) are 4, 2, 1, 2, 1 h(s), respectively. For the MTJD system, the greater the shipping demand, the shorter the delivery cycles for the temperature range. However, comparing the two systems, the delivery cycles for TRs 2, 3, 4 under TMVD are much longer than the MTJD system because the carrier should accumulate a greater shipping volume to realize economies of scale with refrigerated vehicles used for only one temperature range. For TR 1, the lowest range, food in this range is most perishable, and its penalty cost per item would be much higher than other temperature range foods when the delivery time-window is violated. Therefore, the optimal delivery cycle is the same in the two systems. For TR 5, the delivery cycle for both systems is 1 h because shipping demand for this temperature range food appears high and frequent during the entire study period.

Table 3
Values of parameters related to carrier.

Symbol	Equipment	Value
f	Fixed cost for dispatching a regular vehicle (NT$)	750
f^r	Fixed cost for dispatching a refrigerated vehicle (NT$)	900
δ_τ	Loading/unloading cost per box (NT$)	50
δ_Γ	Loading/unloading cost per cabinet (NT$)	100
V_τ	Cold box capacity (L)	90
V_Γ	Cold cabinet capacity (L)	936
ϕ_r	Energy cost per cold box (NT$) (TRs 1, 2, 3, 4, 5)	(95, 91, 90, 86, 83)
Φ_r	Energy cost per cold cabinet (NT$) (TRs 1, 2, 3, 4, 5)	(950, 900, 850, 800, 750)
F^r	Energy cost per refrigerated vehicle (NT$) (TRs 1, 2, 3, 4, 5)	(998, 956, 945, 903, 871)

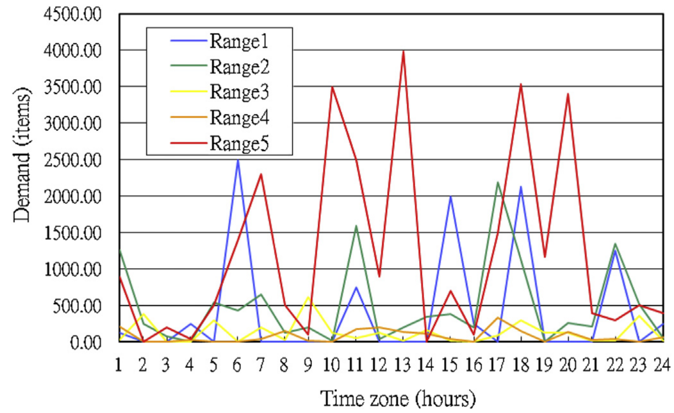

Fig. 2. Time-dependent demand for different temperature range foods.

Table 4 also compares different costs for the MTJD and TMVD systems with percentage of total cost. For both systems, inventory costs account for the highest percentage of the total cost. However, the inventory cost for MTJD is NT$1,351,631, which is much lower than that for TMVD, NT$3,104,008. This indicates that using the MTJD system can reduce the time difference between when the shipper orders the food and when the carrier dispatches the food. Hence, the carrier cannot only lower the inventory cost but also enhance the service level to increase competitiveness. As for transportation cost, there exists a tradeoff between transportation and inventory costs, which are linked by vehicle dispatching frequency (or delivery cycle). However, the transportation cost in this study depends only on the total vehicle dispatching frequency; transportation cost varying with routing distance is not taken into account, as discussed in Section 2. Therefore, the tradeoff between transportation and inventory costs is less obvious. Furthermore, the transportation cost for TMVD, NT$54,750, is lower than for MTJD, NT$65,000, due to the lower dispatching frequencies for TRs 2, 3 and 4. As regards penalty costs, as shown in Table 4, the TMVD system results in many more penalties, NT$2,711,689, than MTJD, NT$448,078, due to increased violations of time-windows. The huge penalty cost in the TMVD system is also related to the lower dispatching frequencies (i.e., longer delivery cycles for TRs 2, 3 and 4). Finally, for energy costs, even though there are more items included in the energy cost in TMVD, the energy cost yielded by that system, NT$42,315, is not significantly greater than MTJD, NT$50,735, due to economies of scale resulting from accumulating shipments for TRs 2, 3 and 4.

In sum, total operation cost as well as inventory and penalty costs are much lower in MTJD than in TMVD. As for transportation and energy costs, the differences between two systems are negligible. Overall, the MTJD system can reduce total cost by NT$3,998,217 over the TMVD system. This indicates that carriers can effectively lower operation costs by using the MTJD system.

Table 4
Overall results from MTJD and TMVD systems.

	MTJD system	TMVD system
Optimal delivery cycles of five temperature ranges (h)	(4,2,1,2,1)	(4,24,24,24,1)
Total cost (NT$)	1,915,445	5,913,662
Transportation cost (NT$)	65,000 (3.39%)	54,750 (0.93%)
Inventory cost (NT$)	1,351,631 (70.56%)	3,104,008 (52.49%)
Penalty cost (NT$)	448,078 (23.39%)	2,711,689 (45.85%)
Energy cost (NT$)	50,735 (2.65%)	43,215 (0.73%)

Table 5 shows the temperature ranges of delivered food and the numbers of stops, vehicles used, and cold boxes/cabinets used for each period for both the MTJD and TMVD systems. Table 6 shows detailed service lists for each period for the MTJD system. The detailed service lists include the retailers served, food items dispatched, and shipping amount for each period. The results in Table 5 show the MTJD system delivered more different temperature range foods and served more retailers than the TMVD system during most periods. This finding indicates that a carrier can unload different temperature range foods simultaneously at a retailer's location using a single regular vehicle, which indicates both unloading time and routing time can be reduced substantially for the retailer and/or carrier.

As Table 5 and Fig. 2 show, for TR 1, vehicles are dispatched before periods with high demand. For example, demand for TR 1 peaks at periods 6, 11, 15, 18, and 22 and vehicles are dispatched for TR 1 at periods 4, 8, 12, 16, 20, and 24. The difference between the peaks of demand and dispatching time is due to expected vehicle travel time during the transportation process, which is listed in Table 2. For TRs 2 and 4, shipping demand appears frequent but is nil during some periods. Such demand patterns result in a vehicle being dispatched every two periods for the MTJD system. However, demand per unit period for these two temperature ranges is much lower than the capacity of a refrigerated vehicle, so carriers using the TMVD system should dispatch these two temperature range foods only once in 24 h (i.e., the entire study period). In that way, refrigerated vehicles of greater capacity can be used and the delivery cost per unit item of food can be reduced due to economies of scale.

For TR 3, shipping demand appears frequently before 12:00 and is nil at some late period. The optimal delivery cycle for TR 3 for the MTJD system is 1 h, which is the shortest cycle among the five temperature ranges, thereby satisfying the frequent demand before 12:00. However, as shown in Table 6, for periods without demand for TR 3, the carrier does not dispatch this food range before such periods. On the other hand, the optimal delivery cycle for TR 3 in

Table 5
Results from each period for the MTJD and TMVD systems.

Time period	MTJD system		TMVD system	
	Delivered ranges	Optimal number of stops, vehicles, cold cabinets and cold boxes	Delivered ranges	Optimal number of stops, vehicles and boxes
1	3,5	(2,2,1,1)	5	(1,1,7)
2	2,3,4,5	(6,3,2,11)	5	(0,0,0)
3	3,5	(1,1,0,3)	5	(1,1,2)
4	1,2,3,4,5	(3,4,3,8)	1,5	(3,4,29)
5	3,5	(3,1,0,10)	5	(1,1,5)
6	2,3,4,5	(4,2,1,6)	5	(2,1,2)
7	3,5	(3,3,2,3)	5	(3,2,18)
8	1,2,3,4,5	(3,2,0,16)	1,5	(1,1,5)
9	3,5	(2,2,1,1)	5	(1,1,1)
10	2,3,4,5	(8,7,6,8)	5	(2,4,35)
11	3,5	(3,3,3,1)	5	(2,3,25)
12	1,2,3,4,5	(9,3,2,9)	1,5	(3,2,12)
13	3,5	(3,5,4,4)	5	(3,4,40)
14	2,3,4,5	(5,2,1,7)	5	(0,0,0)
15	3,5	(2,2,1,1)	5	(1,1,6)
16	1,2,3,4	(6,9,8,7)	1,5	(3,6,45)
17	3,5	(3,3,2,2)	5	(1,2,15)
18	2,3,4,5	(8,3,1,16)	5	(4,1,4)
19	3,5	(3,2,1,4)	5	(2,2,11)
20	1,2,3,4,5	(7,5,3,17)	1,5	(3,4,32)
21	3,5	(2,1,0,6)	5	(1,1,4)
22	2,3,4,5	(5,3,2,7)	5	(1,1,3)
23	3,5	(2,1,0,10)	5	(1,1,5)
24	1,2,3,4,5	(2,1,0,4)	1,2,3,4,5	(10,4,24)

Table 6
Results of stop locations for each period for the MTJD system.

Period	Delivered ranges	Stop codes (food category code, number of units of food)
1	3	10(5,20;6,40)
	5	9(9,200)
2	2	1(4,20); 2(2,100;4,400); 4(2,50;4,200); 10(2,100;3,20;4,100); 9(4,40)
	3	2(5,300;6,300); 9(5,30;6,50)
	4	5(8,500); 9(7,50;8,25); 10(7,200)
3	5	10(10,20)
4	1	1(1,5); 9(1,10); 10(1,100)
	2	9(2,10;3,50); 3(2,50;4,200); 10(2,100)
	4	9(7,10); 10(7,30;8,100;9,20)
5	3	3(5,50;6,200); 9(5,200;10,50); 10(5,20;6,40)
6	2	3(3,150); 10(4,30;3,100); 2(4,200)
	4	9(8,150;7,50)
	5	3(10,100); 9(9,200)
7	3	4(5,100;6,300)
	5	4(9,400); 5(10,100); 10(10,50)
8	2	9(3,50); 10(2,100;4,100)
	3	10(5,20;6,40)
	4	10(7,200); 5(8,400)
	5	9(10,50)
9	3	6(5,300;6,300); 9(5,250;6,200)
	5	9(9,50)
10	2	7(2,20); 9(2,150); 10(2,100;3,50); 1(3,500); 6(2,200;4,100)
	3	4(5,150); 10(5,20)
	4	7(8,40); 8(7,30); 9(7,150;8,200); 10(7,40)
	5	2(10,200); 6(10,150)
11	3	1(6,150)
	5	9(10,50); 10(10,200)
12	1	10(1,30)
	2	1(4,15); 2(2,100); 10(2,100;4,150)
	3	9(5,150); 10(5,20)
	4	3(8,50); 4(7,60); 5(7,100); 6(7,90); 10(8,100); 2(7,100); 8(8,50); 9(7,80)
	5	2(9,50); 9(9,200); 10(9,200)
13	3	10(6,50)
	5	7(9,40;10,20); 9(10,250); 10(10,120)
14	2	9(4,50;3,150); 10(3,100;2,50)
	3	9(6,200); 10(5,120)
	4	3(7,150); 5(8,100); 4(8,100); 10(7,50)
15	3	10(6,40)
	5	9(9,100;10,50)
16	1	10(1,80;1,80); 7(1,10); 1(1,5)
	2	10(4,100;2,100); 1(3,500); 2(2,100;3,50;4,400)
	4	6(8,20); 9(8,50;7,250); 10(7,200)
	5	1(9,50)
17	3	1(6,150); 10(5,20;6,40)
	5	9(10,150)
18	2	1(4,20); 6(4,200); 7(3,120); 9(2,200); 10(3,150)
	3	6(5,400)
	4	3(7,120); 4(7,70); 9(8,150)
	5	2(9,400;10,90); 5(10,120); 9(10,50); 10(9,70)
19	3	9(5,150); 10(6,40)
	5	4(9,80); 10(10,100)
20	1	9(1,50)
	2	2(2,50); 4(2,50); 10(3,100;2,100); 8(4,100)
	3	2(6,80); 4(5,100); 10(5,20)
	4	6(7,100); 9(7,50;8,200); 10(7,40;8,20); 7(7,20)
	5	6(10,150); 8(10,100); 9(9,200;10,50)
21	3	9(6,50); 10(10,40)
22	2	2(4,200); 9(3,200); 10(3,100;4,100;2,100); 1(2,80;4,40); 6(3,50;4,150)
	3	10(6,40;7,50)
	5	1(10,30)
23	3	9(5,250;6,200); 10(5,120)
	5	9(10,50)
24	1	10(1,10)
	2	10(3,20)
	3	10(6,40)
	4	5(8,200); 9(7,200); 10(7,30)
	5	9(9,200)

the TMVD system, 24 h, is much longer than for the MTJD system due to its considerably smaller shipments during most periods. Finally, for TR 5, its high and frequent shipping demand leads to more frequent dispatching for both systems.

Table 5 also lists the numbers of stops, vehicles, and containers. This information can highlight the content of shipments in each period. Except for period 24, the numbers of stops for MTJD are greater than for TMVD because food for TRs 2, 3, 4 is not dispatched during periods 1–23 in the TMVD system. For TMVD, food of TRs 2, 3, and 4 is only dispatched at period 24. Hence, the carrier has to stop at many more locations to deliver food in these ranges. Therefore, the number of stops for TMVD is greater than for MTJD at period 24. The results noted in Table 6 enable a carrier to effectively prepare the fleet, cold cabinets, and boxes for each period.

6. Conclusion

This study develops a mathematical programming model that can determine the optimal delivery cycle for each temperature range food by taking into account time-dependent demand for different temperatures range foods. Though the proposed model, time-varying demand and equipment usage can be analyzed (i.e., demand uncertainty and equipment are dealt with using a multi-periods approach, and costs for different carrier sizes can be determined). The proposed models provide effective tools to determine delivery cycles and dispatching lists for carriers with time-dependent demand by assessing the impact of transportation and inventory costs, as well as energy consumption for temperature control and delivery time-windows, and those resultant costs.

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Nomenclature

D_r: delivery cycle of temperature range r food
y_{sijt}: time when food i, needed by retailer j at period t, leaves distribution center
n: natural number
k_t: number of vehicles dispatched at period t
f: fixed cost for dispatching a regular vehicle
$N_{rt\tau}$: number of temperature range r cold boxes used at period t
$N_{rt\Gamma}$: number of temperature range r cold cabinets used at period t
δ_τ: loading/unloading cost per cold box
δ_Γ: loading/unloading cost per cold cabinet
C_L: loading/unloading cost of MTJD system
φ_r: energy cost per temperature range r box
Φ_r: energy cost per temperature range r cabinet
C_E: energy cost of MTJD system
V_τ: capacity of unit cold box
Q_{ijt}: amount of food i needed by retailer j at period t
γ_i: temperature range in which food i needs to be stored
V_Γ: capacity of unit cold cabinet
C_T: transportation cost of MTJD system
C_I: inventory cost of MTJD system
y_{fijt}: time when food i, needed by retailer j at period t, arrives at distribution center
β_i: inventory cost per unit of time, item of food i
u_{ijt}: lower bound of the soft time-window specified by retailer j who needs food i at period t
s_{ijt}: upper bound of the soft time-window specified by retailer j who needs food i at period t
U_{ijt}: the earliest acceptable time for early arrival of food i, needed by retailer j at period t
S_{ijt}: the latest acceptable time for late arrival, of food i, needed by retailer j at period t
c_i: penalty cost due to violating the earliest and latest acceptable times in the time-window for each item of food i
ρ_j: expected travel time from distribution center to retailer j's location
H_i: value of unit item of food i
d_i: ratio of penalty to food i value
v_i: exponent parameter of penalty cost function of food i
C_{P1}: penalty cost for food i needed by retailer j at period t
C_P: penalty cost of MTJD system
$M_{r,n}$: time interval during which the carrier accumulates temperature range r food to dispatch at nD_r
m: number of periods

$$\varepsilon_{ijt} = \begin{cases} 0 & \text{if penalty for food } i, \text{ needed by retailer } j \text{ at period } t, \text{ is } Q_{ijt} c_i \\ 1 & \text{otherwise} \end{cases};$$

N_t^r: number of normal containers used for temperature range r food at period t of TMVD system
V_N: capacity of one normal container
δ: loading/unloading cost per normal container
C_T': transportation cost of TMVD system
k_t^r: number of temperature range r vehicles dispatched at period t
f^r: fixed cost for dispatching a temperature range r vehicle
F^r: energy cost for using a temperature range r vehicle
t_N: time duration to unload a container from vehicle
α_r: cost for loss of energy per unit of time, temperature range r vehicle
C_E': energy cost of TMVD system
$G(Q_{ijt})$: probability that Q_{ijt} items of food i, ordered by retailer j at period t, perished due to opening the cargo hold per unit of time
C_I': inventory cost of TMVD system
ℓ: number of temperature ranges
X_r: average duration between two shipping demands for temperature range r
ϖ_r^X: average shipping demand during X_r
n': smallest natural number such that $n'X_r > V_\tau$
Z_0: initial temperature of the SA algorithm
A: feasible solution
z: objective function
Z_x: temperature of the SA algorithm at the xth move
π: random variable for determining direction of adjusting delivery cycle
A': adjacent solution
π_1: random variable for determining whether A should be replaced by A'
A^*: optimal solution