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Optimizing fleet size and delivery scheduling for multi-temperature food distribution

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ABSTRACT

In light of the demand for high-quality fresh food, transportation requirements for fresh food delivery have been continuously increasing in urban areas. Jointly delivering foods with different temperature-control requirements is an important issue for urban logistic carriers who transport both low temperature-controlled foods and normal merchandise. This study aims to analyze and optimize medium- and short-term operation planning for multi-temperature food transportation. For medium-term planning, this study optimizes fleet size for carriers considering time-dependent multi-temperature food demand. For short-term planning, this study optimizes vehicle loads and departure times from the terminal for each order of multi-temperature food, taking the fleet size decided during medium-term planning into account. The results suggest that carriers determine departure times of multi-temperature food with demand–supply interaction and deliver food of medium temperature ranges with priority because delivering such food yields more profit.

1. Introduction

In light of the demand for high-quality fresh food, transportation requirements for fresh food delivery have been continuously increasing in urban areas. As such, jointly delivering foods with different temperature-control requirements is an important issue for urban logistic carriers who transport both low temperature-controlled foods and normal merchandise. One of the most important problems carriers encounter is determining a departure time from the terminal for each order of food that has delivery time constraints. These decisions, though restricted by the fleet capacity of carriers, affect the cost and quality of shipping services, especially for perishable food.

Compared with normal goods, perishable food needs strict temperature control and less travel time during the shipping process due to product characteristics, such as a short shelf life and quality decay over time and with fluctuating temperatures. The Industrial Technology Research Institute of Taiwan developed a multi-temperature joint delivery (MTJD[1]) system to distribute food of different temperature ranges in the same vehicle, which enables carriers to ship a variety of multi-temperature foods simultaneously. Unlike traditional refrigerated vehicles, which maintain vehicle compartment temperatures using an engine and compressors, the MTJD system maintains temperatures by using replaceable cold accumulators (eutectic plates) in standard cold boxes or cabinets that are loaded into regular vehicles. In this way, the temperatures in the cold boxes are specified for different requirements and are not changed during door openings. In addition, the combination of temperature ranges in the vehicle can also be easily changed. Kuo and Chen [1] pointed out a way of using the MTJD model in which carriers could

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1 MTJD: multi-temperature joint delivery.

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markedly reduce the logistical costs of handling frequent deliveries in small lots using less than truckload (LTL) transportation, while maintaining customer satisfaction.

This study aims to analyze and optimize medium- and short-term operation planning for multi-temperature food transportation. For medium-term planning, this study optimizes fleet size for carriers considering time-dependent multi-temperature food demand. As for short-term planning, for daily operations, this study optimizes vehicle loads and departure times from the terminal for each order of multi-temperature food, taking the fleet size decided during medium-term planning into account. As mentioned earlier, with the MTJD system, the combination of temperature ranges in the vehicle can be easily changed based on demand. That characteristic allows the MTJD technique to easily deal with the stochastic and dynamic nature of the problem. Furthermore, this study divides the study duration into many small periods. Thus, time-varying demand and delivery volume can be analyzed using a multi-periods approach with high-level accuracy, and the stochastic and dynamic nature of the problem can be considered for multi-temperature food delivery scheduling. Shipping charges are also optimized for jointly delivering multi-temperature food, taking into account dynamic demand patterns and demand–supply interactions between carriers and shippers. In this study, carriers are defined as the logistics contractors who deliver food ordered by general retailers. These carriers have terminals for temporary food storage and own vehicles and temperature controlling equipment that is used to deliver food to retailers. On the other hand, shippers in this study are general retailers in urban areas that sell fresh food to customers in the city, so food delivery times and shipping charges influence their profits and willingness to consign in the future. This study explores demand–supply interaction and constructs a mathematical programming model to determine optimal fleet size and departure times from the terminal for each order, as well as shipping charges for jointly distributing multi-temperature food by maximizing the carrier's profits.

For research related to mathematical modeling for perishable food transportation, Hsu et al. [2] constructed a stochastic vehicle routing problem with time windows (SVRPTW) model to obtain optimal delivery routes, loads, and fleet dispatching and departure times for delivering perishable food from a distribution center. Osvald and Stirn [3] modeled the distribution problem between the distribution centers and the customers (retailers) as a vehicle routing problem with time windows and with time-dependent travel-times (VRPTWTD). Chen et al. [4] proposed a nonlinear mathematical model to consider production scheduling and vehicle routing with time windows for perishable food products in the same framework. Hsu and Liu [5] constructed a binary integer-programming model to determine suitable techniques and the food handling volume required for maximization of cost-efficiency in a hierarchical hub and spoke (H/S) network.

Although many researchers have discussed the importance of food temperature control during the transit process, except for Kuo and Chen [1] and Hsu and Liu [5] there is little research that addresses the application of the MTJD technique. Furthermore, Kuo and Chen [1] did not formulate a mathematical model for analyzing optimal delivery strategies for jointly delivering different temperature range foods using the MTJD system. Hsu and Liu [5] did not discuss dispatching time under time-dependent demand or take into account the demand–supply interaction between the carrier and shippers. To fill the gap, this study focuses on analyzing a joint distribution system operation strategy by considering the costs of carriers, transportation demand, and acceptable shipping charges with a time-dependent demand pattern.

The reminder of this paper is organized as follows. Section 2 describes the model formulation for fleet-size optimization, and Section 3 describes the optimal departure time programming under optimized fleet size and demand–supply interaction. A numerical example is provided in Section 4 to illustrate the application of the model. Finally, conclusions and suggestions are summarized in Section 5.

2. Mathematical programming model for the optimal fleet size

Previous studies have developed fleet-size optimization models to discuss the effects of fleet size on carriers' operating profits. Following the formulation of a fleet-size optimization model by Papier and Thonemann [6], this study constructs an analytical model to determine the optimal fleet size for carriers providing multi-temperature food delivery services. This study focuses on the delivery scheduling of a single distribution center. Therefore, in this study, the whole fleet is used by the same terminal and all orders are distributed from the same place.

Under time-dependent demand, if a carrier owns enough vehicles for peak demand at all times, all orders of food can be delivered in time but many vehicles sit idle during periods with little demand. On the other hand, if the number of vehicles is only sufficient for periods with little demand, even maximizing vehicle capacity would result in loss of revenue due to demand during peak periods. For the sake of simplicity, this study defines the demand time as the middle of a soft time window. For food i ordered by retailer j at time t, with the lower and upper bounds of a soft time window, u_{ijt} and s_{ijt}, respectively, the demand time is $(u_{ijt} + s_{ijt})/2$. To estimate the number of needed vehicles at each period, this study initially assumes that food i ordered by retailer j at time t would leave the terminal at a period that is nearest to (uijt + sijt)/2. After determining fleet size, the departure time would be adjusted through the departure time programming model presented in Section 3.

However, in practice, widths of time windows may be three or four hours. According to Hsu et al. [2], for a soft time window, shippers set the earliest and latest acceptable times for early and late arrival while consigning. Let U_{ijt} and S_{ijt} denote the earliest and latest acceptable times for arrival of food i ordered by retailer j at time t, respectively; the choice set of departure times from the terminal for this order includes several periods and depends on the widths of time slots between U_{ijt} and S_{ijt}. For example, for an order with the earliest and latest acceptable times being 8:00 and 11:00 AM, respectively, if the routing time is within one hour, then the carrier can distribute this order either at 7:00, 8:00, 9:00 or 10:00 AM. Therefore, for those orders with the same demand time, the carrier can allocate them to be distributed at several different periods to optimize delivery. In such a way, not only can the number of vehicles needed be reduced but vehicle capacity utilization can be maximized at most periods.

However, it follows the initial assumption that, if food always leaves the terminal at demand time, then the needed fleet capacity would be overestimated. Nevertheless, before the departure time of each order is optimized, how to allocate food with the same time window to be distributed at different periods is unknown. Therefore, to avoid overestimating the number of needed vehicles, for food i ordered by retailer j at time t with the earliest and latest acceptable arrival times, U_{ijt} and S_{ijt}, respectively, this study divides it into $(U_{ijt} - S_{ijt})$ orders and allocates them to be uniformly distributed at each period between U_{ijt} and S_{ijt} while counting shipping demand for optimizing fleet size. This division is only for determining fleet size; the departure time of each order will be optimized by the programming model in Section 3, which ensures the food ordered by the same retailer with the same time window will be all delivered at the same period.

Let $\beta_m(\Omega)$ denote the fraction of demand lost with a fleet size of Ω vehicles at period m. The fraction of demand filled at period m is $1 - \beta_m(\Omega)$. We use capacity utilization to compute the fraction of demand lost; therefore, $\beta_m(\Omega)$ can be expressed as

$$\beta_m(\Omega) = 1 - \frac{(\Omega\chi)}{\sum_i \sum_j \sum_t \mu^m_{ijt} Q_{ijt} V_i \Big/ (S_{ijt} - U_{ijt})}, \tag{1}$$

where χ denotes vehicle capacity; Q_{ijt} represents the amount of food i ordered by retailer j at time t; V_i represents the volume of unit food i. Symbol μ^m_{ijt} is a binary variable. For food i ordered by retailer j at time t, if $U_{ijt} \leqslant m < S_{ijt}$, $\mu^m_{ijt} = 1$; otherwise, $\mu^m_{ijt} = 0$. This variable is for the order division mentioned earlier. Furthermore, the expected profit function for the carrier for the entire study duration with fleet size Ω, $\pi(\Omega)$, can be formulated as the difference between expected revenue and vehicle holding and idling costs

$$\pi(\Omega) = \sum_m \left[\sum_i \sum_j \sum_t \left(\mu^m_{ijt} Q_{ijt} V_i \sum_r \varpi_{i,r} p_r \right) \right] (1 - \beta_m(\Omega)) - c_1 \Omega - \sum_m c_2 I_m, \tag{2}$$

where c_1 and c_2 denote the holding cost per vehicle for the entire study duration and the idling cost per vehicle per period, respectively. The relationship between ordering time and possible departure time of food i ordered by retailer j at time t can be described by the binary variable, μ^m_{ijt}, as mentioned earlier. Symbol $\varpi_{i,r}$ is also a binary variable; if food i should be stored in temperature range r, $\varpi_{i,r} = 1$; otherwise, $\varpi_{i,r} = 0$. Therefore, the shipping charge per unit volume of food i can be calculated as $\sum_r \varpi_{i,r} p_r$. Symbol I_m denotes the number of idling vehicles at period m, which is estimated by the difference between fleet capacity and distributed volume at period m as Eq. (3).

$$I_m = \left\lfloor \frac{\Omega\chi - \sum_i \sum_j \sum_t \mu^m_{ijt} Q_{ijt} V_i \Big/ (S_{ijt} - U_{ijt})}{\chi} \right\rfloor. \tag{3}$$

The objective is to find the optimal fleet size, Ω^*, that maximizes expected profit. The expected profit function is concave in the fleet size because $\beta_m(\Omega)$ enters the expected profit function with a negative sign. Even the optimal solution might not be unique; this study follows Papier and Thonemann [6] to choose the smallest optimal fleet size, Ω^*, as the solution which yields $\min\,[\pi(\Omega + 1) - \pi(\Omega) < 0]$.

3. Mathematical programming model for the optimal departure time

This study deals with time-dependent multi-temperature food shipping demand and demonstrates how the departure time of each order from the terminal and shipping charges influence operation costs of the carrier, satisfaction of shippers, and shipping demand under demand–supply interactions. This section further explores these influences by devising a mathematical programming model for determining the optimal departure time of each order from the terminal and shipping charges for each temperature range. Assuming the carrier is seeking to maximize profits, the model is formulated by considering the relationship between shipping demand, shipping charges, operation costs of the carrier, and the fleet size optimized by the model in Section 2.

3.1. Retailers' willingness to consign food to object carrier

In practice, shipping charges depend only on shipping volume, temperature range, and time window when the food is consigned and delivered within the same city. This study focuses on the distribution system in a metropolitan area where retailers are densely distributed. Therefore, we assume unit shipping charges for all temperature ranges are not related to transportation distance but only to temperature range. Without considering competition among carriers, the upper bounds of shipping charges are only influenced by the consignment behavior of retailers. In reality, retailers only consign their food shipments when the shipping charges are acceptable; that is, the shipping charges for each temperature range should provide an acceptable profit for selling the food. Let ψ_i denote the expected price of selling food i, and p_r denote the shipping charge for unit volume of temperature range r food, and V_i represent the volume of unit food i. The expected profit for selling food i can be expressed as $(\psi_i - F_{ij} - V_i p_r)$, where F_{ij} is the cost, excluding shipping charges, at which retailer j sells food i. Let R_{ij} represent the minimal profit for selling food i, which is accepted by retailer j, then the upper bound of shipping charges can be obtained from the constraint $(\psi_i - F_{ij} - V_i p_r) \geqslant R_{ij}$. Thereby, the constraint for ensuring shipping charges for each temperature range acceptable can be constructed as

$$p_r \leqslant (\psi_i - F_{ij} - R_{ij})/V_i. \tag{4}$$

The total number of food shipments consigned to the carrier by retailers not only depends on shipping charges but also service level, which means delivery time in this study. If the delivery time is not within the earliest and latest bounds of time windows and makes the release time too short to sell the food, the retailers will withdraw their orders. Let ω_{ijt} be a binary variable, then $\omega_{ijt} = 1$ if retailer j consigns food i to the carrier at time t; otherwise, $\omega_{ijt} = 0$. The demand of the retailers' shipping orders can be constructed as

$$\omega_{ijt} = \begin{cases} 1 & \text{if} \quad (y^s_{ijt} + \rho_m) \in [U_{ijt}, S_{ijt}] \quad \text{and} \quad p_r \leqslant (\psi_i - F_{ij} - R_{ij})/V_i \quad \forall i, \\ 0 & \text{if} \quad (y^s_{ijt} + \rho_m) \notin [U_{ijt}, S_{ijt}] \quad \text{or} \quad p_r > (\psi_i - F_{ij} - R_{ij})/V_i \quad \forall i, \end{cases} \tag{5}$$

$$q_{ijt} = \omega_{ijt} Q_{ijt}, \tag{6}$$

where y^s_{ijt} is the departure time from the terminal of food i ordered by retailer j at time t; symbol Q_{ijt} denotes the demanded amount of food i ordered by retailer j at time t; q_{ijt} represents the amount of food i that carrier dispatches to retailer j at time y^s_{ijt}. $(y^s_{ijt} + \rho_m)$ is the time that food i arrives at the retail store j. Symbol ρ_m represents the average vehicle travel time from terminal to retailers during period m. Eq. (5) describes the relationship between shipping charges, service level (i.e., delivery time), as well as shipping demand. That is, if food can be delivered after the earliest acceptable time for early arrival or before the latest acceptable for late arrival with acceptable shipping charges, shippers would consign the shipment to the carrier. On the other hand, if one of the conditions, shipping charge, or service level, is not acceptable for a shipper, this shipper would not consign the shipment to that carrier.

3.2. Operation cost of MTJD system

Daganzo [7] suggested that all costs incurred by cargoes from origin to destination should be taken into account, regardless of who pays them. Therefore, transportation costs and inventory costs are regarded as two of the major factors in this study. Furthermore, we extend the cost formulation to include electric power costs for storing temperature-controlled food during vehicle routing time and penalty costs for violating delivery time windows. Therefore, for carriers on the supply side, the costs considered for multi-temperature logistics in this study are inventory, transportation, electric power, and penalty costs. Inventory costs are time and storage costs for food in the terminal; the transportation cost is related to vehicle usage and operations; the electric power cost is for temperature control during the transit process. Finally, a penalty cost exists when the delivery time window is violated. Let y^s_{ijt} denote the time that food i ordered by retailer j at time t leaves terminal. The purpose of the model is to find the optimal departure time for each order of food (i.e., $y^s_{ijt}, \forall i, j, t$) and shipping charge for each temperature range (i.e., $p_r, \forall r$) by maximizing the carrier's profit. The cost function formulation is as follows.

3.2.1. Inventory cost

The inventory cost includes the costs for food storage and temperature control in the terminal. Let y^f_{ijt} denote the time that food i ordered by retailer j at time t arrives at the terminal. Symbol B_i represents the inventory cost of unit food i per unit time, which contains costs for storage and temperature control in the terminal. The storage cost depends on the volume of food, and cost for temperature control depends on both volume and temperature range in which the food belongs. Hence, the inventory cost, C_{Inv}, can be formulated as:

$$C_{Inv} = \sum_i \sum_j \sum_t q_{ijt} V_i B_i (y^s_{ijt} - y^f_{ijt}). \tag{7}$$

3.2.2. Transportation cost

The transportation cost includes fixed and variable costs for using vehicles, and loading/unloading costs for cold boxes and cabinets. The fixed cost includes maintenance cost, vehicle depreciation cost, and drivers' salaries. Let f denote the fixed cost for dispatching one vehicle, and the number of vehicles used at period m be a_m, then the total fixed transportation cost during the entire study duration can be formulated as $\sum_m a_m f$.

The variable transportation cost depends on routing distance. This study calculates total vehicle travel distance by continuous approximation [7]. Let n_m denote the number of shippers a carrier serves at period m, and the average shipping volume for each shipper at period m is $\bar{D}_m$; σ represents the number of shippers per unit area; $\bar{L}_m$ denotes the average vehicle load at period m. Thereby the average number of shippers served by the same vehicle at period m, $\bar{n}_m$, can be calculated as $\bar{n}_m = \bar{L}_m / \bar{D}_m$, and the total routing distance of the whole fleet can be formulated as $2E(\Delta) n_m / \bar{n}_m + k n_m / \sqrt{\sigma}$, where $E(\Delta)$

denotes the expected distance from terminal to the shippers' retailer stores. Symbol k is a constant; $k \approx 0.57$ when the distance is calculated by Euclidean Metric, and $k \approx 0.82$ if the distance is computed as Metric. Let the fuel cost per unit routing distance be O. The fuel cost in this study is for delivery truck fuel due to vehicle routing. The total variable transportation cost at period m can be calculated as $[2E(\Delta)n_m/\bar{n}_m + kn_m/\sqrt{\sigma}]O$.

The loading/unloading costs depend on the number of cold boxes and cabinets used for delivery. Let $N_{rm\tau}$ and $N_{rm\Gamma}$ denote the number of cold boxes and cold cabinets used for temperature range r food at period m, respectively. Symbols δ_τ and δ_Γ represent the loading/unloading costs for a cold box and cabinet, respectively, then the loading/unloading cost at period m can be expressed as $\delta_\tau N_{rm\tau} + \delta_\Gamma N_{rm\Gamma}$, and the total loading/unloading costs during the entire study duration can be shown as $\sum_m \sum_r (\delta_\tau N_{rm\tau} + \delta_\Gamma N_{rm\Gamma})$. In sum, the transportation cost, C_{Tra}, can be formulated as

$$C_{Tra} = \sum_m \left[a_m f + [2E(\Delta)\bar{n}_m/n_m + kn_m/\sqrt{\sigma}]O + \sum_r (\delta_\tau N_{rm\tau} + \delta_\Gamma N_{rm\Gamma}) \right]. \tag{8}$$

The numbers of cold boxes and cabinets not only depend on total volume of distributed food but also depend on capacity utilizations, which are affected by unit volume, shape, or some other characteristics of food (e.g. breakable). To simplify the model, this study assumes all food has rectangular packaging and does not consider other factors affecting capacity utilization. The capacity utilizations for all containers are taken into account as constants. Let γ_τ and γ_Γ denote the capacity utilizations of cold boxes and cabinets, respectively; symbol V_τ and V_Γ denote the capacity of a cold box and cabinet, respectively, and the constraint related to cold boxes and cabinets can be constructed as

$$N_{rm\tau} V_\tau + N_{rm\Gamma} V_\Gamma \geqslant \sum_i \sum_j \sum_t \theta_{ijt}^m q_{ijt} V_i \quad \forall m, r \tag{9}$$

where θ_{ijt}^m is a binary variable. If the departure time from the terminal for food i ordered by retailer j at time t is m, $\theta_{ijt}^m = 1$; otherwise, $\theta_{ijt}^m = 0$. Let V'_τ and V'_Γ denote the volume of a cold box and cabinet, respectively. Since fleet size is limited as the optimal fleet size, as mentioned earlier, the constraint related to fleet capacity and cold box/cabinet usage can be expressed as

$$\sum_r (N_{rm\tau} V'_\tau + N_{rm\Gamma} V'_\Gamma) \leqslant \chi\Omega^* \quad \forall m. \tag{10}$$

3.2.3. Electric power cost

The electric power cost is the cost for temperature control during vehicle routing time, which depends on temperature and equipment usage time. The usage time can be estimated by routing distance and average vehicle speed; therefore, the electric power cost can be calculated as

$$C_{Ene} = \sum_m (\delta_\tau N_{rm\tau} + \delta_\Gamma N_{rm\Gamma})[2E(\Delta)\bar{n}_m/n_m + kn_m/\sqrt{\sigma}]O/v_m, \tag{11}$$

where φ_r and Φ_r denote the electric power cost of a cold box and cabinet for storing temperature range r food per unit time, respectively. Symbol v_m represents the average vehicle speed at period m.

3.2.4. Penalty cost

Regarding the penalty cost, according to Hsu et al. [2], if perishable food delivery time is not within the time window but still acceptable, the penalty cost can be calculated as follows. Symbol s_{ijt} denotes the upper bound of the time window for food i ordered by retailer j at time t, and ρ_m represents the average vehicle travel time from terminal to retailers at period m. Then the length of delay is $(y_{ijt}^s + \rho_m - s_{ijt})$, and its penalty cost would be $b_{ijt} q_{ijt} P_i d_{ij} \left(y_{ijt}^s + \rho_m - s_{ijt} \right)^{\zeta_i}$, where b_{ijt} is a binary variable. If food i ordered by retailer j at time t could not be delivered within the soft time window, $b_{ijt} = 1$; otherwise, $b_{ijt} = 0$. Symbol P_i denotes the value of food i, d_{ij} represents the ratio of penalty to value of food i for retailer j, and ζ_i is a parameter of food i, $\zeta_i > 1$. Add up all penalties for all delayed food deliveries during the entire study duration and the total penalty cost, C_{Pen}, can be calculated as

$$C_{Pen} = \sum_m \sum_i \sum_j \theta_{ijt}^m b_{ijt} q_{ijt} P_i d_{ij} \left[\lambda (y_{ijt}^s + \rho_m - s_{ijt}) \right]^{\zeta_i}, \tag{12}$$

where λ is a parameter, which is set for the delay being less than one period. Without this parameter, the penalty may decrease while the delay increases; thus, it does not conform to the definition of penalty. This study calculates vehicle travel time at period m, ρ_m, using continuous approximation [7], as mentioned earlier. Furthermore, the number of vehicles used at period m can be estimated as $(n_m \bar{D}_m)/\bar{L}_m$ by total distributed volume and average vehicle load. This estimated number of vehicles used describes the relationship between customer demand, vehicle load, and travel time, and it should be close to vehicle usage in reality, which is mentioned earlier in the section of transportation cost calculation. The ρ_m can be expressed as

$$\rho_m = \frac{2E(\Delta)n_m/\bar{n}_m + kn_m/\sqrt{\sigma}}{v_m(n\bar{D}_m/\bar{L}_m)}. \tag{13}$$

Furthermore, ρ_m can be simplified as

$$\rho_m = \lfloor 2E(\Delta) + k\bar{n}_m/\sqrt{\sigma} \rfloor / v_m. \tag{14}$$

Then the carrier's profit can be formulated as $\sum_i \sum_j \sum_t q_{ijt} V_i p_r - (C_{Inv} + C_{Tra} + C_{Ene} + C_{Pen})$.

3.3. Formulation of the optimal problem

A nonlinear programming problem is formulated here for determining the optimal departure time for each order of multi-temperature food by maximizing profit subject to delivery time windows and demand–supply interaction. The interaction process is demonstrated in Section 3.4. From the discussion above, the nonlinear programming problem for maximizing profit through the entire study duration is as follows. The decision variables are the departure time for each order of food (i.e., $y^s_{ijt}, \forall i, j, t$) and shipping charge for each temperature range (i.e., $p_r, \forall r$).

$$\max \sum_i \sum_j \sum_t q_{ijt} V_i p_r - (C_{Inv} + C_{Tra} + C_{Ene} + C_{Pen}), \tag{15a}$$

s.t.

$$p_r \leqslant (\psi_i - F_{ij} - R_{ij})/V_i \quad \forall r, \tag{15b}$$

$$C_{Inv} = \sum_i \sum_j \sum_t q_{ijt} V_i B_i (y^s_{ijt} - y^f_{ijt}), \tag{15c}$$

$$C_{Tra} = \sum_m \left[a_m f + [2E(\Delta)\bar{n}_m/n_m + kn_m/\sqrt{\sigma}]O + \sum_r (\delta_\tau N_{rm\tau} + \delta_\Gamma N_{rm\Gamma}) \right], \tag{15d}$$

$$C_{Ene} = \sum_m (\delta_\tau N_{rm\tau} + \delta_\Gamma N_{rm\Gamma}) [2E(\Delta)\bar{n}_m/n_m + kn_m/\sqrt{\sigma}] O / v_m, \tag{15e}$$

$$C_{Pen} = \sum_m \sum_i \sum_j \theta^m_{ijt} b_{ijt} q_{ijt} P_i d_i \left[\lambda (y^s_{ijt} + \rho_m - s_{ijt}) \right]^{\zeta_i}, \tag{15f}$$

$$\rho_m = [2E(\Delta) + k\bar{n}_m/\sqrt{\sigma}]/v_m, \tag{15g}$$

$$N_{rm\tau} V_\tau + N_{rm\Gamma} V_\Gamma \geqslant \sum_i \sum_j \sum_t \theta^m_{ijt} q_{ijt} V_i \quad \forall m, r \tag{15h}$$

$$\sum_r (N_{rm\tau} V'_\tau + N_{rm\Gamma} V'_\Gamma) \leqslant \chi \Omega * \quad \forall m. \tag{15i}$$

Eq. (15a) represents the objective function that maximizes profit through the study duration. Eq. (15b) expresses the upper bound of the shipping charge for each temperature range. Eqs. (15c)–(15f) define the inventory, transportation, energy and penalty costs as Eq. (7), (8), (11), and (12), respectively. Moreover, Eq. (15g) represents the travel time estimating function as Eq. (14). Eq. (15h) requires that the total capacity of cold boxes and cabinets must be equal to or larger than the total volume of shipments for each temperature range at each period. Furthermore, Eq. (15i) requires the total volume of cold boxes and cabinets at each period be equal to or smaller than the fleet capacity.

3.4. Demand–supply interaction

After determining the fleet size using the model described in Section 2, this study decides departure time from the terminal for each order of food and shipping charges for each temperature range. The demand–supply interaction between departure time and shipments are analyzed by the model described above. On the demand side, shipping volume is estimated by aggregating shippers' carrier choices. The shipping volume of food i ordered by retailer j at time t is estimated by Eq. (5) and (6) and used as input parameters for the departure time determining programming model on the supply side (Eqs. (15a)–(15i)), and the departure time and shipping charges determined by Eqs. (15a)–(15i) affect shippers' choices. This study explores the relationship between shipping demand and service level (i.e., departure or delivery time) for multi-temperature food under demand–supply interaction using an iterative algorithm. First, shipping demand for each temperature range food is initialized using known data values, then the optimal shipping charges for each temperature range and departure time for each order are determined by the mathematical programming model to maximize the carrier's profit (Eqs. (15a)–(15i)). Then shipping demand of food i ordered by retailer j at time t is estimated by Eqs. (5) and (6). The aforementioned steps conclude the first "round" of interaction; this process is repeated for many more rounds. The process continues until the total shipping volume and shipping charges for all temperature range foods are unchanged, and the shipping charges for all temperature ranges of food and departure times for all shipments are determined.

This study adopted the Simulated Annealing algorithm to solve the optimal departure time for each order of food. We made trial runs to examine the time consumption and possible results; the travel times from terminal to retailer for the trial solutions are all between 0.6 and 1.5 h (s). In practice, delivery time windows usually exceed three hours; therefore, this study sets the initial solution as the earliest acceptable time for early arrival of food (i.e., the departure time of the initial solution for food i ordered by retailer j at time t is U_{ijt}). To solve the problem effectively, we sets the time for solving the proposed model to be 0.5 h.

4. Numerical example

This section presents a numerical example to demonstrate the application of the model constructed in Sections 2 and 3. This example covers an area of 500 km^2 and comprises an extraction of the characteristics of customers, which include time window constraints and shipping demand. In this case, there are 1177 orders of 20 kinds of food from 95 different retailers consigned to the object carrier; the food is divided into five different ranges: Cryogenic (below −30 °C), Frozen (−30 °C to −18 °C), Chilled (−2 °C to +2 °C), Cold (0–7 °C), and Fresh (18 °C, constant) as shown in Table 1. The carrier provides two service alternatives – delivery within a time window on the same day or the day after ordering, respectively. On each operating day, the carrier deals with orders with a time-window in the morning, which is ordered on the previous day, and orders with a time-window in the afternoon, which is ordered on the previous day or the same day. When same-day call-in orders are received, the carrier can add the orders to the demand list, and then resolve the overall scheduling problem within 30 min, which is the problem solving time mentioned in Section 3. This study assumes one operating day, namely 24 h, as the entire study duration, with the unit of time for the study being 1 h. The length of a period is one hour and the carrier dispatches vehicles at the beginning of each hour. Customers' time windows are generated between 1:00–24:00 based on food characteristics.

4.1. Time-dependent demand

The temporal pattern of demand during the entire study is shown in Fig. 1. In Fig. 1, the demand time is approximately estimated as the middle of the time window, and the figure also shows shipping demand for most temperature range foods peaks during 7:00–9:00 and 14:00–16:00 because shippers are restaurants, supermarkets, or convenience stores in the city. Such delivery time windows ensure they have time to process and/or sell fresh food to their customers at lunch and dinner times. For the differences among five ranges, Range 3 has the most demand volume because this range contains the majority of perishable food in the example; the demand of Range 1, which contains only sashimi, is most centralized due to its short shelf life and the fact that it is affected by temperature much more than other food. Base values for parameters in the cost functions are estimated by data collecting and interviewing manufacturers of temperature control equipment, as listed in Table 2. The temporal pattern of road speeds is estimated by data from the Taipei City Department of Transportation, as shown in Fig. 2, which reveals rush hours.

Table 1
Initial values of food.

Food code	Food	Temperature range	V_i(L)	P_i (NT$)	B_i (NT$)	ζ_i
1	Sashimi	1	22	950	0.008	2.20
2	Ice cream	2	10.5	65	0.007	1.05
3	Frozen steamed buns with stuffing	2	12	350	0.007	1.20
4	Frozen steamed dumplings	2	12	250	0.007	1.20
5	Frozen vegetables	2	15	200	0.007	1.50
6	Frozen meat	2	15	400	0.007	1.50
7	Fish	3	20	700	0.006	2.00
8	Duck	3	17	400	0.006	1.70
9	Chicken	3	18	500	0.006	1.80
10	Mutton	3	18	600	0.006	1.80
11	Pork	3	18	500	0.006	1.80
12	Beef	3	20	800	0.006	2.00
13	Ham	4	13	50	0.005	1.30
14	Bean curd	4	15	60	0.005	1.50
15	Milk	4	14	800	0.005	1.40
16	Juice	4	14	500	0.005	1.40
17	Vegetables	4	16	500	0.005	1.60
18	Chocolate	5	10.5	150	0.004	1.05
19	Cookie	5	12	45	0.004	1.20
20	Soft drink	5	12	60	0.004	1.20

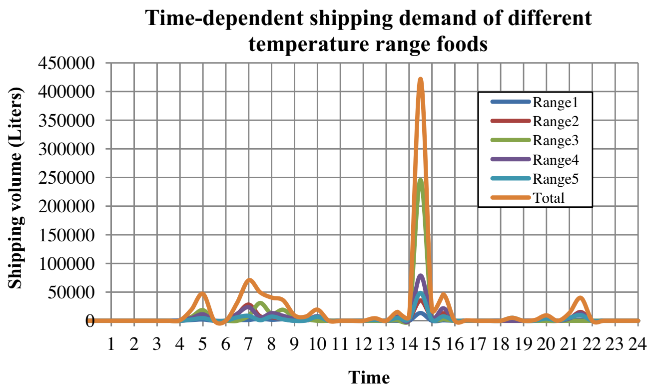


Fig. 1. Time-dependent shipping demand for different temperature range foods.

Table 2
Value of parameters related to carriers.

Symbol	Definition	Value
χ	Vehicle capacity (m^3)	16
f	Fixed cost for dispatching a vehicle (NT$)	200
δ_τ	Loading/unloading cost per box (NT$)	15
δ_Γ	Loading/unloading cost per cabinet (NT$)	45
V_τ/V'_τ	Cold box capacity/volume (L)	90/194
V_Γ/V'_Γ	Cold cabinet capacity/volume (L)	936/2118
ϕ_r	Energy cost per cold box per hour (NT$) (temperature range 1, 2, 3, 4, 5)	1.14, 1.026, 0.988, 0.775, 0.540
Φ_r	Energy cost per cold cabinet per hour (NT$) (temperature range 1, 2, 3, 4, 5)	3.42, 3.078, 2.964, 2.326, 1.619

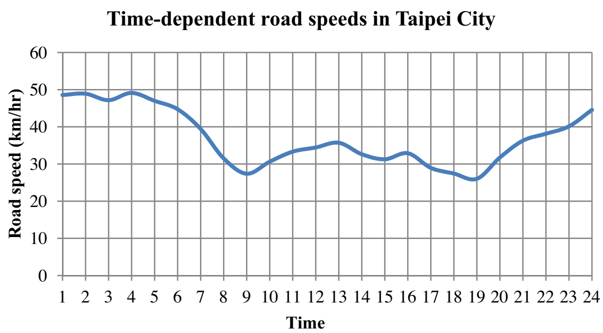
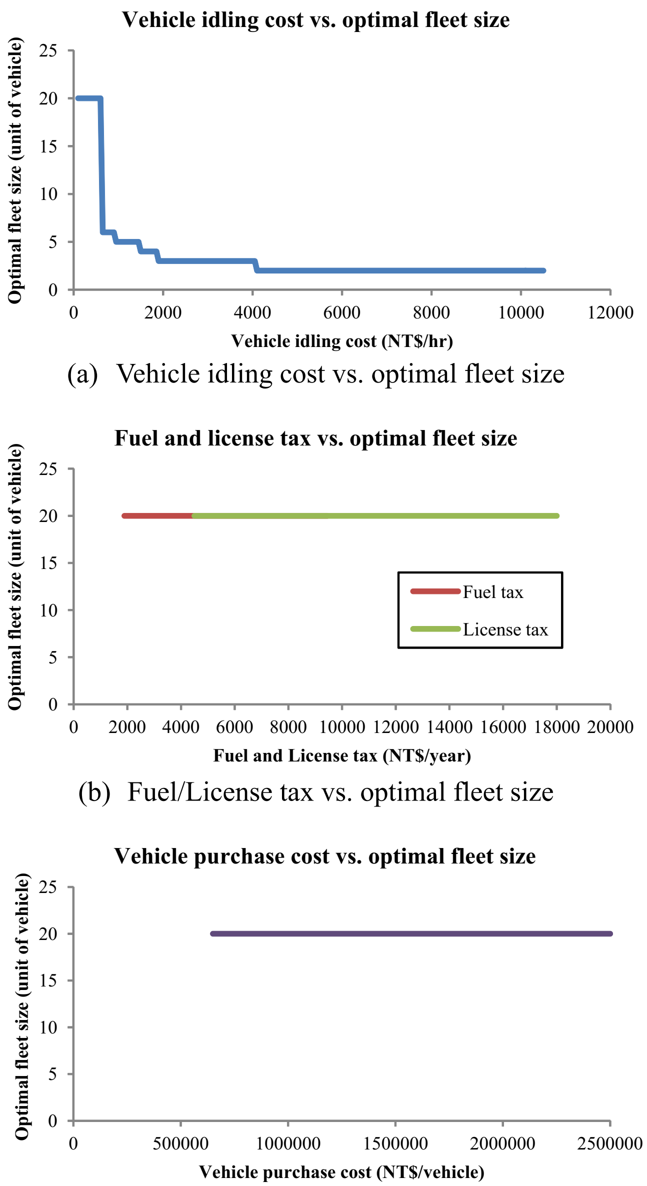


Fig. 2. Time-dependent road speeds in Taipei City.

4.2. Optimal fleet size

Vehicle holding cost was estimated by fuel tax, license tax, and vehicle purchase cost divided by its lifetime. The fuel tax is levied by the government and is based on the air displacement of vehicle. The optimal fleet size for the carrier is 20 vehicles when the vehicle purchase cost and idling cost per period are NT$1,550,000 and NT$500, respectively, with the demand pattern shown in Fig. 1. Moreover, the vehicle handling and idling costs vary with socioeconomic conditions, business cycles, and government policy. This study examines the relationships among these two costs and optimal fleet size for the MTJD system. However, we do not discuss the influence of socioeconomic conditions on the vehicle handling and idling costs, and only analyze the sensitivity of the optimal fleet size due to changes in these two costs. Fig. 3 illustrates vehicle idling cost per period and vehicle handling cost vs. optimal fleet size, respectively. As Fig. 3 shows, vehicle handling cost (fuel tax, license tax, and vehicle purchase cost) does not affect the optimal fleet size but vehicle idling cost has a marked affect. In addition, as shown in Fig. 3, as the idling cost increases, the optimal fleet size decreases at a lower rate. This is because, under the same demand pattern, since the fleet size is optimized, the number of idling vehicles is decreased, and the optimal fleet size is less sensitive to unit idling cost variations. These imply that, under sufficient purchase budgets, the carrier should



(a) Vehicle idling cost vs. optimal fleet size

(b) Fuel/License tax vs. optimal fleet size

(c) Vehicle purchase cost vs. optimal fleet size

Fig. 3. Vehicle idling/holding cost vs. optimal fleet size.

determine fleet size based on idling cost; the higher the idling cost, the smaller the fleet size, and the more discretion when considering adding vehicles.

4.3. Shipping charges

To calculate the upper bound of the acceptable shipping charge for each temperature range, the study collects all data related to expected profit and other costs for all of shippers. To maximize profits, the carrier should choose the highest upper bound of all acceptable shipping charges to be the optimal scheme. In practice, for the service of delivering within a time window on the same and the day after ordering, carriers set the charges for the latter at 0.83 times the former. Therefore, this study assumes the charges for next day delivery are 0.8 times those for same day delivery. The results after rounding are shown in Table 3. Because this study does not consider competition between carriers, the results in Table 3 may be a little higher than service charges in practice. However, the results are still reasonable as compared with practice.

Table 3
Optimal shipping charges for different temperature range foods and delivery alternatives (Unit: NT$/Liter).

Temperature range/service	Delivery on the same day of ordering	Delivery on the next day of ordering
Range 1 (below −30 °C)	2.0	1.7
Range 2 (−30 °C to −18 °C)	1.2	1.0
Range 3 (−2 °C to +2 °C)	1.0	0.8
Range 4 (0–7 °C)	0.7	0.5
Range 5 (18 °C∼)	0.5	0.4

Table 4
Delivered temperature ranges at different periods from results obtained without and with demand supply interaction.

Period	Delivered temperature ranges	
	Result without demand–supply interaction	Result with demand–supply interaction
1	/	/
2	/	/
3	/	/
4	1,2,3,4,5	1,2,3,4,5
5	1,2,3,4,5	1,2,3,4,5
6	1,2,3,4,5	1,2,3,4,5
7	1,2,3,4,5	1,2,3,4,5
8	1,2,3,4,5	1,2,3,4,5
9	1,2,4,5	1,2,3,4,5
10	2,4	2,4,5
11	4,5	4
12	2,3,4,5	2,3,4,5
13	1,2,3,4,5	1,2,3,4,5
14	1,2,3,4,5	1,2,3,4,5
15	1,2,3,4,5	1,2,3,4,5
16	1,2,3,4,5	2,4,5
17	5	2,5
18	2,4,5	4,5
19	1,2,4,5	1,2,4,5
20	1,2,4,5	1,2,4,5
21	/	/
22	/	/
23	/	/
24	/	/

4.4. Delivery scheduling

Table 4 shows the delivered temperature ranges at different periods for cases without and with demand–supply interaction, respectively. The results show that the carrier in this example should distribute four or five temperature range foods jointly at most periods, for both cases. This implies that the proposed model can help carriers provide on-time delivery by distributing different temperature range foods jointly. Thus, the probability of violating time windows can be reduced, and shippers can receive different temperature range foods simultaneously, which results in lower unloading times for both shippers and carriers. The difference between the two cases appears during 9:00–11:00 as well as 16:00–18:00, as shown in Table 4. This is because some orders that are demanded during 13:00–15:00 but delivered at 11:00 or 16:00 are abandoned or moved to be delivered at other periods after rounds of interactions. In that way the penalty cost and other delivery costs can be reduced.

Figs. 4 (a) and (b) show the distributed volume for different temperature range foods at different periods under optimal departure time programming without and with demand–supply interaction, respectively. Fig. 4(a) shows the results where a carrier abandons shipments that cannot be delivered within an acceptable time in the case without demand–supply interaction. Fig. 4(b) shows the results when solving with demand–supply interaction. Comparing Fig. 4 with Fig. 1, it shows that time-dependent demand for different temperature ranges can be smoothed by the proposed model. The shipping demands during 13:00–14:00, which is shown in Fig. 1, are dispersed and distributed during 11:00–16:00, which is shown in Fig. 4(a). However, since some orders would be withdrawn due to not being delivered within the time windows, as Eq. (5) describes (i.e., a segment of the fleet capacity at the periods the carrier delivers these orders is vacant), there might be room for improvement in the optimal solution of departure times of each order. For this reason, the demand–supply interaction described in Section 3.4 is needed.

In Fig. 4(b), the results obtained with demand–supply interaction show that some food distributed before 12:00 or after 15:00, as shown in Fig. 4(a), are withdrawn or moved to other periods; thereby, the penalty and other delivery costs for these

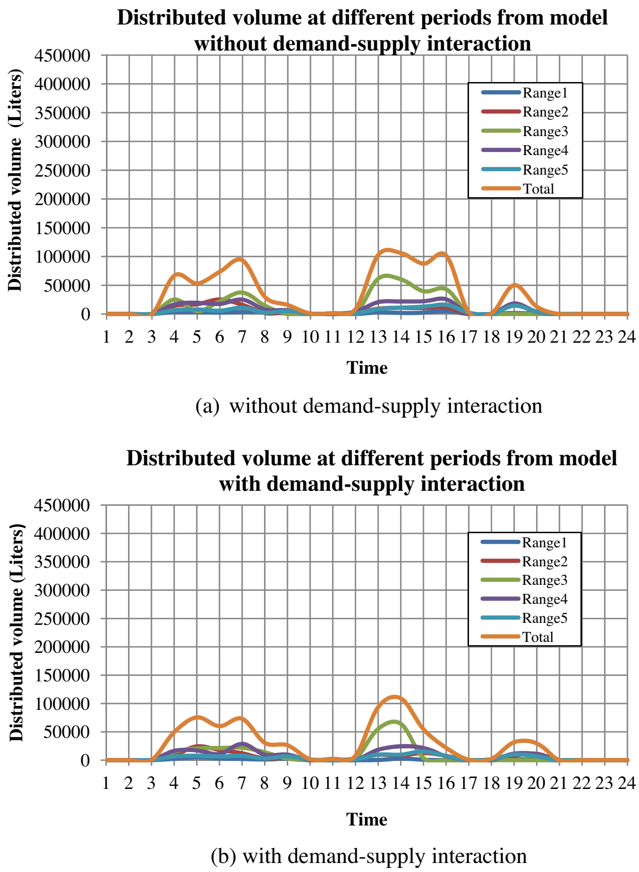


Fig. 4. Optimal distributed volume of various temperature range foods at different periods.

shipments can be saved. Except for 13:00–14:00, shipping demand during 7:00–9:00 is also markedly higher than other periods while not exceeding fleet capacity. However, since shipping demand does not exceed fleet size, the distributed volume before 9:00 does not change significantly, but there is a little variation after rounds of interactions. For the same reason, the distributed volume at 19:00 obtained without demand–supply interaction is allocated to be distributed at 19:00 and 20:00 in the case with demand–supply interaction.

Table 5 shows the distributed volume and function values from results obtained without and with demand–supply interaction, respectively. In the case without demand–supply interaction, the difference between initial volume and revised volume shows that the distributed volumes of all temperature range foods are less than the initial shipping demands due to abandoning shipments that cannot be delivered within acceptable time. Furthermore, the distributed volume of all temperature range foods is reduced after demand–supply interaction. The reason for this is that this study reprograms the optimal departure time for accepted orders and abandons some orders after rounds of interaction. However, this study does not explore how to increase shipping demand; it only discusses how to deliver. The proposed model can decide which orders should be abandoned under limited fleet capacity until the accepted orders yield maximal profit. Moreover, as shown in Table 5, Temperature Range 3 food reduced most markedly after rounds of interactions; this is because Temperature Range 3 food accounts for the highest initial shipping demand among all ranges, especially during peak periods. Since this range accounts for the highest shipping demand, the abandoned volume after rounds of interactions is greater than other ranges. Secondly, the distributed volume of Temperature Ranges 1 and 5 are reduced more than Temperature Ranges 2 and 4 after rounds of interactions. One reason for this is that delivering Range 1 food consumes the most electric power and highest inventory cost because of it requiring the lowest temperature, and delivering Range 5 food yields least revenue due to it having the lowest shipping charge among all ranges. On the contrary, the costs and revenue of delivering Temperature Range 2 and 4 foods are medium among all ranges. This implies that, under limited fleet capacity and time-dependent shipping demand, the carrier should abandon some orders of the lowest or normal temperature range foods at peak periods; thus, other range foods that yield more profit (i.e., require less cost or yield more revenue) can be delivered on time and the total profit of the carrier can be maximized.

As regards service level, this study uses the time window violation rate as its measure. We calculate this rate as the ratio of the number of orders not delivered within soft time windows to the total number of delivered orders. The time window

Table 5
Comparison of distributed volume and function values from results obtained without and with demand supply interaction.

	Result without demand–supply interaction		Result with demand–supply interaction
Distributed volume (L)	*Initial volume*	*Revised volume*	
Temperature range 1	34,320	32,450	23,320
Temperature range 2	156,546	141,611	130,556
Temperature range 3	361,142	310,658	222,296
Temperature range 4	233,600	212,255	190,675
Temperature range 5	131,193	112,184	103,349
Total distributed volume	916,801	809,157	670,195
Inventory cost (NT$)		68,127 (14.76%)	55,748 (16.40%)
Penalty cost (NT$)		92,973 (20.15%)	67,023 (19.71%)
	Time window violating rate: 6.02%		Time window violating rate: 3.31%
Transportation cost (NT$)		169,401 (36.71%)	136,727 (40.21%)
Vehicle cost (NT$)		30,600 (6.63%)	25,600 (7.53%)
Oil cost (NT$)		91,311 (19.79%)	71,137 (20.92%)
Loading/uploading cost (NT$)		47,490 (10.29%)	39,990 (11.76%)
Electric power cost (NT$)		130,969 (28.38%)	80,528 (23.68%)
Total cost (NT$)		461,470	340,026
Total revenue (NT$)		613,825	499,009
Total profit (NT$)		152,355 (33.02%)	158,983 (46.76%)

Note: Parentheses denote percentage of total cost.

violation rate obtained with demand–supply interaction is 3.31%, which is much lower than that obtained without demand–supply interaction, namely 6.02%, as shown in Table 5. This implies that service level can be effectively enhanced after rounds of interaction, which helps maintain the carrier's shipping volume and revenue over time.

4.5. Costs and profits

Table 5 also compares different costs and profits, using percentage of total operation cost, for the results obtained without and with demand–supply interaction, respectively. As shown in Table 5, the penalty cost obtained with demand–supply interaction is NT$67,023, which is lower than that obtained without demand–supply interaction, namely NT$92,973. The other three costs are also reduced and the profits increased because some orders that cannot be delivered within the time windows are withdrawn and the accepted orders are allocated to be distributed more effectively after rounds of interactions. Therefore, optimal departure time solving with demand–supply interaction results in higher profits than models without demand–supply interaction. The findings imply that, with demand–supply interactions, not only service level but profit can be improved.

As regards the cost structure shown in Table 5, with demand–supply interaction, the transportation cost accounts for the highest percentage (40.21%) of the total cost. Transportation cost includes cost for dispatching vehicles, fuel consumption, and loading/unloading shipments, which account for 7.53%, 20.92%, and 11.76% of the total cost, respectively. The high percentage due to oil consumption implies that carriers should decide food departure times and terminal locations carefully so as to reduce transportation costs and maintain service level at the same time. If routing distance can be decreased, not only the transportation cost but the electric power cost for controlling temperature during transit can be reduced. Moreover, the electric power cost accounts for the second highest percentage (23.68%) due to the power consumed by freezers; therefore, carriers should use freezers to accumulate cold during night hours when there are lower power prices. Furthermore, fuel and electric power consumption are the major sources of greenhouse gas emissions for most countries. Since many governments set emission reduction targets or levy an emissions tax, carriers should use high energy efficiency vehicles and freezers to reduce energy consumption. In that way, carriers can reduce not only operation costs but greenhouse gas emissions while maintaining service levels. Furthermore, it can reduce emission costs if the carrier is levied a carbon tax. Regarding inventory cost, since joint delivery decreases the time that food waits in the terminal, this cost accounts for only 16.40% of the total cost, which is the lowest among all costs, as shown in Table 5. Finally, the percentage penalty cost accounts for 19.71%. We suggest that carriers deal with shippers whose food is not delivered within the time windows as a priority in the following days to avoid losing these customers due to a high violation rate.

4.6. Other detail results

Table 6 lists the distributed food and quantities, as well as the retailers served in the case with demand–supply interaction during 13:00–14:00, which is the period with the most distributed volume, as shown in Fig. 4. The results show that huge multi-temperature shipments are distributed to a few shippers at these peak periods. This finding implies that, at periods with peak demand, carrier should deliver shipments of huge size with priority because they can yield more revenue and the cost of violating their time windows might be large.

Table 6
Distributed orders from results obtained with demand–supply interaction.

Period	Temperature ranges	Stop codes and distributed food
13	1	13
		[1(15)]
	2	21
		[2(60),3(50),4(50),5(100),6(100)]
		59
		[2(60),3(50),4(50),5(100),6(100)]
	3	13
		[7(60)]
		21
		[7(200),8(120),9(450),10(160),11(300),12(200)]
		59
		[7(100),8(60),9(50),10(40),11(100),12(100)]
		83
		[7(200),8(40),9(50),10(20),11(100),12(200)]
	4	21
		[13(100),14(70),15(150),16(200),17(200)]
		59
		[13(50),14(30),15(50),16(60),17(50)]
		80
		[(13(60),14(10),15(60),16(20),17(50)]
		83
		[(13(40),14(10),15(40),16(20),17(50)]
	5	21
		[18(40),19(100),20(100)]
		59
		[18(40),19(80),20(80)]
		80
		[18(30),19(100),20(100)]
		83
		[18(10),19(80),20(80)]
14	1	14
		[1(30)]
		60
		[1(60)]
		95
		[1(40)]
	2	60
		[2(60),3(60),4(60),5(60),6(60)]
		67
		[2(12),3(20),4(20),5(20),6(20)]
		95
		[2(60),3(40),4(40),5(40),6(40)]
	3	11
		[7(80),8(20),9(70),10(20),11(80),12(80)]
		12
		[7(10),8(2),9(12),10(3),11(15),12(12)]
		14
		[7(80),8(20),9(70),10(20),11(80),12(70)]
		60
		[7(300),8(140),9(350),10(140),11(250),12(250)]
		92
		[7(200),8(50),9(150),10(50),11(150),12(150)]
		95
		[7(100),8(50),9(100),10(50),11(100),12(100)]
	4	11
		[13(40),14(50)]
		12
		[13(5),14(13)]
		14
		[13(40),14(30),17(80)]
		60
		[13(100),14(60),15(80),16(200),17(200)]
		67
		[13(15),14(5),15(50),16(50),17(30)]
		78
		[13(20),14(30),15(30),16(30),17(60)]
		92

(*continued on next page*)

Table 6 (*continued*)

Period	Temperature ranges	Stop codes and distributed food
		[13(50),14(20),15(40),16(60),17(80)]
		95
		[13(50),14(20),15(30),16(40),17(70)]
	5	60
		[18(80),19(200),20(200)]
		67
		[18(5),19(50),20(50)]
		92
		[18(30),19(60),20(60)]
		95
		[18(30),19(40),20(40)]

Note: Parentheses denote food code and amount.

Table 7
Equipments usage and vehicle travel time from results obtained without and with demand–supply interaction.

Period	Result without demand–supply interaction				Result with demand–supply interaction			
	Number of vehicles (units)	Average vehicle travel time (h)	Number of cold boxes (units)	Number of cold cabinets (units)	Number of vehicles (units)	Average vehicle travel time (h)	Number of cold boxes (units)	Number of cold cabinets (units)
1	0	/	0,0,0,0,0	0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
2	0	/	0,0,0,0,0	0,0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
3	0	/	0,0,0,0,0	0,0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
4	12	0.653	8,6,3,2,3	3,15,27,18,7	10	0.652	7,6,9,11,3	2,9,15,17,7
5	10	0.684	9,3,4,10,6	3,18,5,20,8	14	0.682	7,1,2,5,5	5,26,22,18,8
6	14	0.719	7,1,10,9,3	2,27,23,18,6	11	0.716	2,4,10,8,1	3,19,22,11,7
7	17	0.816	11,1,1,9,10	3,17,40,26,11	13	0.813	4,1,5,9,5	2,13,23,30,8
8	6	1.019	8,7,3,3,6	3,1,15,8,2	6	1.016	3,1,9,3,2	1,3,14,10,3
9	3	1.176	8,3,0,2,9	0,3,0,7,5	5	1.170	9,4,1,6,5	2,4,3,10,7
10	1	1.049	0,4,0,7,0	0,0,0,0,0	1	1.046	0,2,0,1,6	0,0,0,0,1
11	1	0.961	0,0,0,5,5	0,0,0,0,1	1	0.961	0,0,0,4,0	0,0,0,2,0
12	2	0.934	0,3,3,6,5	0,2,1,4,1	2	0.931	0,3,8,10,5	0,2,3,0,1
13	19	0.897	1,10,10,2,1	3,9,65,22,9	17	0.896	4,4,11,7,6	0,10,58,19,10
14	19	0.981	10,7,6,4,10	1,11,64,23,11	20	0.981	1,5,7,2,4	3,8,68,26,10
15	16	1.025	9,2,4,8,8	2,11,42,23,13	10	1.024	10,8,1,2,7	0,13,4,23,16
16	19	0.975	6,3,1,4,3	5,12,46,27,17	4	0.974	0,2,0,4,9	0,8,0,7,7
17	1	1.108	0,0,0,0,5	0,0,0,0,2	1	1.106	0,7,0,0,2	0,0,0,0,0
18	1	1.169	0,7,0,7,2	0,0,0,0,0	1	1.168	0,0,0,7,11	0,0,0,0,1
19	9	1.233	2,3,0,8,7	2,16,0,19,15	6	1.230	2,6,0,5,9	2,8,0,12,10
20	3	1.011	8,3,0,2,6	0,4,0,4,4	6	1.009	8,11,0,6,5	0,11,0,11,7
21	0	/	0,0,0,0,0	0,0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
22	0	/	0,0,0,0,0	0,0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
23	0	/	0,0,0,0,0	0,0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
24	0	/	0,0,0,0,0	0,0,0,0,0	0	/	0,0,0,0,0	0,0,0,0,0
Average	6.375	0.965	4,3,2,4,4	1,6,14,9,5	5.33	0.963	2,3,3,4,4	1,6,10,8,4

The numbers of vehicles, cold boxes, and cold cabinets needed for all periods without and with demand–supply interaction are shown in Table 7. The fourth, fifth, eighth, and ninth columns of Table 7 are the numbers of cold boxes and cabinets used for each temperature range without and with demand–supply interaction, respectively. For example, for the results obtained without demand–supply interaction, at Period 4, as shown in the fourth column of Table 7, the carrier used eight, six, three, two, and three cold boxes for Temperature Ranges 1–5, respectively. Because cold cabinets have greater economies of scale, the number of required boxes is proportionally less than the ratio of cabinets to boxes in terms of their capacity (936/90). As shown in Table 7, at many periods, not all of the 20 vehicles of the fleet are dispatched. During these off-peak periods, the carriers can use the idle vehicles to transport non-perishable cargos with longer time windows, such as books or clothes. As for vehicle travel time from the terminal to retailers, comparing Fig. 2 with Table 7, travel time during rush hours is longer than other periods. This finding implies that carriers should reduce travel time by avoiding routing on congested roads, especially at periods with high shipping demand. The above discussion can be referenced through research regarding vehicle routing problems and terminal location analysis.

5. Conclusions

This study aims to formulate a mathematical programming model to solve the optimal fleet size and food departure times for jointly distributing different temperature range foods. The numbers of vehicles, cold boxes, and cabinets needed for each delivery period can be solved by the model. The model also estimates the average vehicle travel time and calculates the optimal shipping charges for each temperature range by maximizing the carrier's profit. A numerical example illustrates the application of the proposed model. The results suggest that carriers determine departure times of multi-temperature food with demand–supply interaction to increase profit. In addition, when shipping demand exceeds fleet capacity, the carrier should deliver food of medium temperature ranges with priority because delivering such food yields more profit. This study formulates the model with a high level of accuracy to analyze the time-dependence of demand and delivery volume but uses rough approximations for distance and road speed at rush-hour to reduce the problem solving time. Future studies may extend the model by enhancing accuracy levels in distance and speed at rush-hour and developing a heuristic to improve solution efficiency simultaneously.

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References

[1] R.C. Kuo, M.C. Chen, Developing an advanced multi-temperature joint distribution system for the food cold chain, Food Control 21 (2010) 559–566.
[2] C.I. Hsu, S.F. Hung, H.C. Li, Vehicle routing problem with time-windows for perishable food delivery, J. Food Eng. 80 (2007) 465–475.
[3] A. Osvald, L.Z. Stirn, A vehicle routing algorithm for the distribution of fresh vegetables and similar perishable food, J. Food Eng. 85 (2008) 285–295.
[4] H.K. Chen, C.F. Hsueh, M.S. Chang, Production scheduling and vehicle routing with time windows for perishable food products, Comput. Oper. Res. 36 (2009) 2311–2319.
[5] C.I. Hsu, K.P. Liu, A model for operational planning for multi-temperature joint distribution system, Food Control 22 (2011) 1873–1882.
[6] F. Papier, U. Thonemann, Queuing models for sizing and structuring rental fleets, Transp. Sci. 42 (2008) 302–317.
[7] C.F. Daganzo, Logistics Systems Analysis, third ed., Springer-Verlag, Berlin, 1999.