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Optimal scheduling for multi-temperature joint distribution under carbon tax

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Abstract: In light of growing environmental concerns, many countries have developed schemes of carbon tax. Accordingly, carriers have to minimize the impact of carbon tax on their profits, and one of the feasible solutions is to reduce emissions through operations. On the other hand, in recent years, multi-temperature joint delivery (MTJD) has become an important issue for carriers. This paper aims to investigate how to optimize delivery schedules considering operations and emission costs due to carbon tax for multi-temperature logistics. Based on prior research, this paper integrates a model to determine a dispatching time for each order in the MTJD system by minimizing a carrier's total spending, which consists of delivery cost and emission cost due to carbon tax. Furthermore, we compare the results obtained with and without carbon tax. The comparisons include cost structures, distribution patterns, and emissions in the two cases. The results show that carbon tax can lessen the effect of fuel consumption on operation cost, and carriers should deliver high density middle temperature ranges food at periods without traffic congestion. Food belonging to the same temperature range should have more centralized distribution when carbon tax exists than the case without emission cost.
Keyword — Green logistics, Multi-temperature joint delivery, Food transportation, Mathematical Programming, Scheduling

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1. INTRODUCTION

In light of growing environmental concerns, governments around the world face pressure to reduce greenhouse gas (GHG) emissions. For this reason, many countries develop schemes of carbon taxes or Emission Trading Systems (ETS) to push industries to lower emissions from their businesses. There are about 40 national jurisdictions and over 20 cities, states, and regions that are putting a price on carbon (Kossoy et al., 2015). In Taiwan, Executive Yuan is planning a policy related to carbon tax. On the other hand, road freight transportation is a major contributor to carbon emissions (Demir, Bektaş, & Laporte, 2014). Accordingly, carriers have to investigate how to minimize the impact of carbon tax on their profits. One feasible solution to reduce emissions is to optimize operations while considering emission costs. Hence, many studies (e.g. Bektaş, Ehmke, Psaraftis, & Puchinger, 2019; Bouchery & Fransoo, 2015; Holguín-Veras et al., 2018; Tang, Wang, Yan, & Hao, 2015; Ugarte, Golden, & Dooley, 2016; Yang, Guo, & Ma, 2016; Zhou & Zhang, 2017) explore the relationship between freight operations and emissions, and then point out that decreasing delivery frequency can reduce greenhouse gas emissions. However, most prior research focus on general logistics, and little research discuss the impact of carbon tax on multi-temperature food joint distribution.

Multi-temperature joint distribution (MTJD) has become one of the most important issues for carriers in recent years. The MTJD technique can deliver foods stored at different temperature ranges by a single regular vehicle with replaceable cold accumulators and standardized cold insulated boxes to maintain precise temperatures (Hsu, Chen, & Wu, 2013). Such a technique provides flexibility to adjust shipping volumes of different temperature ranges in the same vehicle. On the other hand, the MTJD system generates greenhouse gases from not only fuel but also electric power consumption and refrigerant leakage, which are not involved in general logistics. This paper aims to investigate how to optimize scheduling of multi-temperature joint distribution considering service level, delivery costs, and emission costs due to carbon tax.

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In the MTJD system, for any given time period, delivery schedule affects distributed weight and volume. Furthermore, distribution patterns vary with time and influence total costs for carriers and emissions from the logistics system. On the other hand, delivery scheduling is restricted by time windows for each order and capacities of fleet, vehicles, and cold boxes for each temperature range. These issues result in complexity for green logistics scheduling for the MTJD, and few studies discussed all issues mentioned above simultaneously. A lot of research investigate cold chain operations, but some of them do not discuss the effects of carbon tax on operations (e.g. Ali, Nagalingam, & Gurd, 2018; M. Chen, Lu, & Liu, 2018; Hsiao, Chen, & Chin, 2017; Hsiao, Chen, Lu, & Chin, 2018). On the other hand, some research explores cold chain with a consideration for emissions but do not explore the difference among various temperature ranges (e.g. Accorsi, Gallo, & Manzini, 2017; Hariga, As'ad, & Shamayleh, 2017; Stellingwerf, Kanellopoulos, Vorst, & Bloemhof, 2018; Stellingwerf, Laporte, Cruijssen, Kanellopoulos, & Bloemhof, 2018). For example, Hsu and Chen (2014) investigated optimal scheduling for the MTJD without considering emissions. W. Chen and Hsu (2015) estimated emissions from the MTJD system without exploring how to optimize scheduling while taking into account carbon tax. Based on prior research, this paper integrates a mathematical programming model to determine delivery schedule in the MTJD system under carbon tax levying, fleet size limit, time-dependent shipping demand, and various traffic conditions. This paper uses a carrier's total spending for delivering multi-temperature food as the objective function to be minimized by departure time from terminal for each order. The total cost of a carrier includes delivery cost and emission cost due to carbon tax in the MTJD system. Furthermore, this paper compares cost structures, distribution patterns, and emissions in cases with and without carbon tax.

Furthermore, some studies investigate cold chain operations taking into account the effects of greenhouse gas emissions. Hariga et al. (2017) presented integrated economic and environmental models for a multi-stage cold supply chain under carbon tax regulation to determine the optimal lot sizing and shipping quantities. Stellingwerf, Kanellopoulos, et al. (2018) assessed benefits of cooperation in temperature-controlled transportation by applying an Inventory Routing Problem (IRP) and comparing different forms of cooperation. Stellingwerf, Kanellopoulos, et al. (2018) proposed an extension of the Load-Dependent Vehicle Routing Problem (LDVRP) model to optimize routing decisions and to account for refrigeration emissions in temperature-controlled transportation systems. Their results showed taking the emissions caused by refrigeration into account improves the estimation of emissions related to temperature-controlled transportation. However, the above studies did not discuss multi-temperature joint distribution and the tradeoff among various temperature ranges.

In the area of multi-temperature joint distribution, several studies explored efficiencies of the MTJD when compared with traditional multi-vehicle distribution (TMVD). Kuo and Chen (2010) presented an MTJD-based model according to the requirements of the food chain and the operations of a carrier in Taiwan. Hsu and Liu (2011) constructed a model to determine multi-temperature logistics techniques and food handling volume required to maximize cost-efficiency in a hierarchical hub-and-spoke network. Hsu et al. (2013) formulated mathematical models to optimize delivery cycles for jointly delivering multi-temperature food using TMVD and MTJD systems. Hsu and Chen (2014) optimized fleet size for a multi-temperature food carrier, then determined vehicle loads and departure times from the terminal for each order. W. Chen and Hsu (2015) estimated greenhouse gas emissions from TMVD and MTJD systems by formulating mathematical models. M. Chen et al. (2018) formulated an integer programming model for consolidation problem for fresh agricultural products in a multi-temperature joint distribution (MTJD) system that was developed to resolve the challenge of timely delivery of small and diverse shipments in food cold chains. Although these studies explore operations of MTJD, and some of them estimate emissions from the MTJD, the effects of carbon tax on the MTJD system were not investigated.

In sum, there is still a lack of research that explores how to optimize scheduling for the MTJD taking into account carbon tax and tradeoff among various temperature ranges. To fill the gap, this paper integrates the delivery scheduling model and emissions estimation functions, which were formulated by Hsu and Chen (2014) and W. Chen and Hsu (2015), respectively. In those two studies, Hsu and Chen (2014) formulated a delivery scheduling model with a high level of accuracy to analyze the MTJD system but did not consider cost of emissions. W. Chen and Hsu (2015) constructed functions to estimate emissions in the MTJD system under time-dependent demand and traffic conditions but they did not explore how emission costs due to carbon tax affects carriers' costs and decisions. In this paper, we integrate the delivery scheduling model with the emission estimation functions. Thus, the optimal delivery time for each order in the MTJD system, which takes into account carbon tax, can be analyzed. This paper compares the difference between cases with and without carbon emission tax, in terms of cost structures, distribution patterns, and emissions for multi-temperature food, under time-dependent shipping demand. Furthermore, this paper discusses the tradeoff among distributions of different temperature ranges food when they are jointly distributed by the same vehicle.

This paper is organized as follows. Section 2 describes the integrated model for optimizing scheduling of multi-temperature joint distribution with a consideration for carbon tax. Section 3 provides a numerical example to illustrate the application of the model. Finally, conclusions are summarized in Section 4.

2. MODEL FORMULATION

This section presents a mathematical programming model for determining the optimal departure time from a terminal for each order of multi-temperature food. We refer to Hsu and Chen (2014) to formulate the delivery cost functions and constraints then use W. Chen and Hsu (2015) to compute emissions from the MTJD system. Although Hsu and Chen (2014) formulated a model to optimize delivery schedules for multi-temperature food, they did not discuss the environmental impact of MTJD. As for W. Chen and Hsu (2015), even though emissions from the MTJD were estimated, they did not explore optimal operations for MTJD considering emission costs due to carbon tax. Because of these shortcomings, this paper further integrates the two cited studies, with the concept that carbon tax levying results in emission costs for carriers. The model assumption, decision variables, objective function, and constraints of the proposed model are described as follows.

2.1 Model Assumption

The proposed logistics system delivers food stored at different temperature ranges. This logistics system is comprised of a carrier and a large number of consignees. The object carrier owns a distribution center and delivers multi-temperature food to consignees. In this system, consignees are retailers in urban areas, and the consignee is also the shipper for each order. We focus on the transport process from terminal to retailers and consider costs and emissions that are influenced by delivery scheduling.

2.2 Decision variables

This paper aims to optimize delivery scheduling while considering carbon tax. Therefore, the decision variable in the proposed model is departure time from terminal for each order of multi-temperature food. Let y^s_{ijt} denote departure time from terminal for food i ordered by consignee j at time t. Thus, the objective function and constraints in the proposed model are determined by the decision variables, $y^s_{ijt}, \forall i, j, t$. The subscripts of decision variables present the attributes of orders. The attributes include codes of food (i), consignee (j), and ordering time (t). In order to calculate shipping volume and weight for each temperature range food at each period, we set a binary variable, θ^m_{ijt}. If departure time from terminal for food i ordered by consignee j at time t is m, $\theta^m_{ijt} = 1$; otherwise, $\theta^m_{ijt} = 0$. Therefore, the value of θ^m_{ijt} depends on y^s_{ijt}. Although both y^s_{ijt} and θ^m_{ijt} can express the decision variables of the proposed model, they are used for distinct situations. The former presents the distribution moment of a specific order, and the latter is set for summing up all shipping volume or weight of a specific temperature range at a specific period.

In the MTJD system, there are many critical items which depend on departure time from terminal for each order. First, shipping volume of temperature range r that carrier dispatch at period m is determined by orders whose departure time are period m with storage temperature range r. Second, number of cold boxes used for temperature range r food at period m can be calculated by dividing shipping volume of temperature range r food at period m by capacity of cold box. Furthermore, number of vehicles used at period m can be computed by dividing total volume of cold boxes by capacity of vehicle. Finally, number of consignees the carrier serves at each period is certainly related to departure time from terminal for each order.

Moreover, shipping volume and cold box usage for each temperature range, vehicle usage, and number of consignees the carrier serves at each period are critical for the costs which are taken into account in this paper. First, warehousing cost depends on how much time that food stay at terminal, and it is determined by arrival and departure time of food at and from terminal, respectively. Second, penalty cost relies on whether food is delivered to consignee within its time window, and delivery time is highly related to departure time from terminal certainly. Third, transportation cost contains costs resulted from vehicle dispatching, vehicle load, routing distance, and cold box usage. In the MTJD system, vehicle dispatching and cold box usage depends on shipping volume for each temperature range food at each period, and vehicle load relies on weight of orders. Furthermore, shipping volume and weight at specific period can be calculated by summing up volume and weight of orders whose departure time from terminal are the same period, respectively. As for routing distance, it can be estimated by number of consignees that carrier serves, and it depends on the decision variable as discussed in the previous paragraph. Fourth, electric power cost depends on vehicle routing time and cold box usage. Vehicle routing time can be estimated by routing distance and road speed. However, routing distance and cold box usage rely on the decision variables as mentioned earlier in this paragraph.

In the MTJD system, the sources of emissions include fuel consumption, electric power consumption, and refrigerant leakage. Fuel consumption depends on routing distance and vehicle load; electric power consumption and refrigerant leakage both can be estimated by vehicle routing time and cold box usage. As discussed earlier, vehicle routing distance and time, vehicle load, and cold box usage all rely on the decision variables of the proposed model. Since emission cost due to carbon tax is based on emissions from the MTJD system, it depends on the decision variables, departure time from terminal of each order of multi-temperature food, too. Based on above discussion, these critical items can be expressed as Eqs. (1)-(6).

$$Q_{m,r} = \sum_i \sum_j \sum_t \theta_{ijt} A_{i,r} q_{ijt} V_i \tag{1}$$
$$N_{m,r} = Q_{m,r}/\beta \tag{2}$$
$$a_m = e \sum_r N_{m,r}/\chi \tag{3}$$
$$n_m = \sum_j \max(\theta_{ijt}, \forall i, t) \tag{4}$$
$$D_m = Q_m/n_m \tag{5}$$
$$\bar{n}_m = \chi/D_m \tag{6}$$

where

- $Q_{m,r}$: total shipping volume of temperature range r food that carrier distributes at period m
- θ_{ijt}^m : a binary variable, if departure time from terminal for food i ordered by consignee j at time t is m , $\theta_{ijt}^m = 1$; otherwise, $\theta_{ijt}^m = 0$
- $A_{i,r}$: a binary variable, if food i is stored at temperature range r, $A_{i,r} = 1$; otherwise, $A_{i,r} = 0$
- q_{ijt} : amount of food i ordered by consignee j at time t
- V_i : volume of unit food i
- $N_{m,r}$: number of cold boxes used for temperature range r at period m
- β : capacity of a cold box
- a_m : number of vehicles used at period m
- e : volume of a cold box
- χ : vehicle capacity
- n_m : number of consignees that carrier serves at period m
- D_m : average shipping volume for each shipper at period m
- $\bar{n}_m$: average number of consignees served by the same vehicle at period m

Eq. (1) sums up temperature range r food which is dispatched at period m. Eq. (2) calculates number of cold box used for temperature range r food at period m. Eq. (3) computes number of vehicles used at period m. Eq. (4) counts number of consignees carrier serves at period m. Eq. (5) and Eq. (6) estimate average shipping volume for each shipper and average number of consignees served by the same vehicle at period m, respectively.

2.3 Objective function

We assume the object carrier is seeking to minimize cost. The objective function is formulated by delivery cost and emission cost due to carbon tax in the MTJD system, which are denoted as $C_{delivery}$ and $C_{emission}$, respectively. Thus, the objective in the proposed model for determining departure time of each order from the terminal is given as Eq. (7), and the calculations of $C_{delivery}$ and $C_{emission}$ are described in Sections 2.3.1 and 2.3.2, respectively.

$$obj = \min(C_{delivery} + C_{emission}) \tag{7}$$

2.3.1 Delivery cost

This paper follows Hsu and Chen (2014) to divide the entire study duration into many small periods and takes into account four types of costs that compose the delivery cost for a carrier who uses the MTJD technique. These four costs are warehousing, transportation, electric power, and penalty costs. We refer to the equations formulated by Hsu and Chen (2014) with essential revisions in accord with emission estimations. The formulations for these four costs are illustrated as follows.

First, warehousing cost is for food storage in the terminal before distribution. Therefore, it includes costs for storage space and temperature control, which depend on time. According to Hsu and Chen (2014), warehousing costs in the MTJD system, C_{Inv}, can be computed as Eq. (8).

$$C_{Inv} = \sum_i \sum_j \sum_t q_{ijt} B_i (y^s_{ijt} - y^f_{ijt}) \tag{8}$$

where

- q_{ijt} : mount of food i ordered by consignee j at time t
- B_i : warehousing cost of unit food i per unit time
- y^s_{ijt} : departure time from terminal of food i ordered by consignee j at time t
- y^f_{ijt} : arrival time at terminal of food i ordered by consignee j at time t

Second, for transportation cost, Hsu and Chen (2014) computed it according to shipping volume but did not consider the influence of payload in terms of weight. However, payload has significant impact on fuel consumption rate, which is the major emission source in the MTJD system. Therefore, we refer to the payload function in W. Chen and Hsu (2015) to calculate fuel consumption in the MTJD system. Thus, transportation cost in the MTJD system, C_{Tra}, can be revised as

$$C_{Tra} = \sum_m \left\{ a_m f + \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] \Gamma_m o_m O + \sum_r \delta N_{m,r} \right\} \tag{9}$$

where

- a_m : number of vehicles used at period m
- f : fixed cost for dispatching a vehicle
- $E(\triangle)$: expected distance from terminal to consignees
- $\bar{n}_m$: average number of consignees served by the same vehicle at period m
- n_m : number of consignees the carrier serves at period m
- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- σ : number of consignees per unit area
- Γ_m : average vehicle payload factor at period m that measures deviation of a vehicle's fuel consumption rate from an average value based on payload
- o_m : fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m, which is road speed at period m
- O : cost per unit fuel consumption
- δ : loading/uploading cost for a cold box at period m
- $N_{m,r}$: number of cold boxes used for temperature range r at period m

In Eq. (9), a_m, $\overline{n}_m$, n_m, $N_{m,r}$ can be substituted by the right hand sides of Eq. (3), (6), (4), (2), respectively. Therefore, Eq. (9) can be expressed through the decision variables, θ^m_{ijt}.

Third, electric power cost results from temperature control during transport process. In the MTJD system, cold accumulators are used in cold boxes for transit, and they consume electric power that results in cost. Therefore, electric power cost depends on number of cold boxes and usage time. According to Hsu and Chen (2014), electric power cost in the MTJD system, C_{Ene}, can be calculated as

$$C_{Ene} = \sum_m \sum_r \left\{ \phi_r N_{m,r} \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] / v_m \right\} \tag{10}$$

where

- ϕ : electric power cost for a temperature range cold box per unit time
- $N_{m,r}$: number of cold boxes used for temperature range at period
- $E(\Delta)$: expected distance from terminal to consignees
- $\overline{n}_m$: average number of consignees served by the same vehicle at period
- n_m : number of consignees the carrier serves at period
- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- δ : number of consignees per unit area
- v_m : road speed at period m

In Eq. (10), $N_{m,r}, \overline{n}_m, n_m$ can be substituted by the right hand sides of Eq. (2), (6), (4), respectively. Therefore, Eq. (10) can be expressed through the decision variables, θ^m_{ijt}.

Finally, penalty cost is compensation for consignees' losses due to violating delivery time windows. According to Hsu and Chen (2014), penalty cost in the MTJD system, C_{Pen}, can be expressed as

$$C_{Pen} = \sum_m \sum_i \sum_j \theta^m_{ijt} b_{ijt} q_{ijt} P_i h_i \left[\lambda(y^s_{ijt} + \rho_m - s_{ijt})\right]^{\xi_i} \tag{11}$$

where

- θ^m_{ijt} : a binary variable, if departure time from terminal for food i ordered by consignee j at time t is m, $\theta^m_{ijt} = 1$; otherwise, $\theta^m_{ijt} = 0$.
- b_{ijt} : a binary variable, if food i ordered by consignee j at time t could not be delivered within soft time window, $b_{ijt} = 1$; otherwise, $b_{ijt} = 0$.
- q_{ijt} : amount of food i ordered by consignee j at time t
- P_i : value of food i
- h_i : ratio of penalty to value of food i for consignee j
- λ : a parameter that is set 0 for delay being less than one period; otherwise, $\lambda = 1$
- y^s_{ijt} : departure time from terminal of food ordered by consignee j at time t
- ρ_m : average vehicle travel time from terminal to consignees at period m
- s_{ijt} : upper bound of time window for food i ordered by consignee j at time t
- ξ_i : a parameter of food i, $\xi_i > 1$

2.3.2 Emission cost

Emission cost is determined by greenhouse gases generated from the MTJD system and carbon tax for unit emission. Let T represent carbon tax for unit emission. Then, total emission cost in the MTJD system, $C_{Emission}$, can be expressed as

$$C_{Emission} = T(G_{Oil} + G_{Ele} + G_{Ref}) \tag{12}$$

where G_{Oil}, G_{Ele}, and G_{Ref} denote emissions from fuel consumption, electric power consumption, and refrigerant leakage, respectively. The relationship between delivery scheduling and each source of emissions in the MTJD system is illustrated as follows.

First, the main source of emissions in the MTJD system is fuel consumption, and greenhouse gases are generated during vehicle routing time. According to W. Chen and Hsu (2015), emissions from fuel consumption in the MTJD system, G_{Oil}, can be calculated as

$$G_{Oil} = \sum_m d_m \Gamma_m o_m \alpha_{Oil} \tag{13}$$

where

- d_m : total vehicle travel distance at period m
- Γ_m : average vehicle payload factor at period m that measures deviation of a vehicle's fuel consumption rate from an average value based on payload
- o_m : fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m, which is road speed at period m
- α_{Oil} : emission factor of unit oil consumption

Following Hsu and Chen (2014), this paper uses continuous approximation (Daganzo, 1999) to estimate routing distance at each period. Thus, total vehicle travel distance at period m, d_m, in Eq. (15) can be expressed as

$$d_m = \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + kn_m/\sqrt{\sigma}\right] \tag{14}$$

where

- $E(\Delta)$: expected distance from terminal to consignees
- $\overline{n}_m$: average number of consignees served by the same vehicle at period m
- n_m : number of consignees the carrier serves at period m
- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- σ : number of consignees per unit area

Eq. (13), the emissions from fuel consumption in the MTJD system, G_{Oil}, can be re-written as Eq. (15) by using Eq. (14).

$$G_{Oil} = \sum_m \left\{ \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + kn_m/\sqrt{\sigma}\right] \Gamma_m o_m \alpha_{Oil} \right\} \tag{15}$$

- $E(\Delta)$: expected distance from terminal to consignees
- $\overline{n}_m$: average number of consignees served by the same vehicle at period m
- n_m : number of consignees the carrier serves at period m
- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- σ : number of consignees per unit area
- Γ_m : average vehicle payload factor at period m that measures deviation of a vehicle's fuel consumption rate from an average value based on payload
- o_m : fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m, which is road speed at period m
- α_{Oil} : emission factor of unit oil consumption

In Eq. (15), $\overline{n}_m$ and n_m can be substituted by the right hand sides of Eq. (6) and Eq. (4), respectively. Therefore, Eq. (15) can expressed through the decision variables, θ_{ijt}^m.

Second, electric power consumption of freezers in the terminal generates greenhouse gas emissions, and these emissions depend on number of cold boxes and usage time. According to W. Chen and Hsu (2015), emissions from electric power consumption by freezer in the MTJD system, G_{Ele}, can be computed as

$$G_{Ele} = \sum_m \sum_r \left(N_{m,r} X_r\right) \left(d_m/v_m + 2\omega N_{m,r}\right) \gamma \alpha_{Ele} \tag{16}$$

where

- $N_{m,r}$: number of cold boxes used for temperature range r at period m
- X_r : number of cold accumulators used for a temperature range r cold box
- d_m : total vehicle travel distance at period m
- v_m : road speed at period m
- ω : loading or unloading time for one cold box
- γ : electric power consumption per unit time for unit cold accumulator
- α_{Ele} : emission factor of unit electric power consumption

Eq. (16), the emissions from electric power consumption by freezer in the MTJD system, G_{Ele}, can be re-written as Eq. (17) by using Eq. (14).

$$G_{Ele} = \sum_m \sum_r (N_{m,r} X_r) \left\{ \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + kn_m/\sqrt{\sigma} \right] /v_m + 2\omega N_{m,r} \right\} \gamma \alpha_{Ele} \tag{17}$$

- $N_{m,r}$: number of cold boxes used for temperature range r at period m
- X_r : number of cold accumulators used for a temperature range r cold box
- $E(\Delta)$: expected distance from terminal to consignees
- $\overline{n}_m$: average number of consignees served by the same vehicle at period m
- n_m : number of consignees the carrier serves at period m
- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- σ : number of consignees per unit area
- v_m : road speed at period m
- ω : loading or unloading time for one cold box
- γ : electric power consumption per unit time for unit cold accumulator
- α_{Ele} : emission factor of unit electric power consumption

Furthermore, in Eq. (17), $N_{m,r}$, $\overline{n}_m$, n_m can be substituted by the right hand sides of Eq. (2), (6), (4), respectively. Therefore, Eq. (17) can be expressed through the decision variables, θ^m_{ijt}.

Freezers in the MTJD system also result in refrigerant leakage. Emissions due to refrigerant leakage include Hydrofluorocarbons (HFCs) and Perfluorocarbons (PFCs). According to W. Chen and Hsu (2015), emissions from refrigerant leakage in the MTJD system, G_{Ref}, can be calculated as

$$G_{Ref} = \sum_m \sum_r (N_{m,r} X_r) (d_m/v_m + 2\omega N_{m,r}) R_r \tag{18}$$

where

- $N_{m,r}$: number of cold boxes used for temperature range r at period m
- X_r : number of cold accumulators used for a temperature range r cold box
- d_m : total vehicle travel distance at period m
- v_m : road speed at period m
- ω : loading or unloading time for one cold box
- R_r : emissions from refrigerant leakage due to accumulating cold for a temperature range r accumulator per unit time

Eq. (18), the emissions from refrigerant leakage in the MTJD system, G_{Ref}, can be re-written as Eq. (19) by using Eq. (14).

$$G_{Ref} = \sum_m \sum_r (N_{m,r} X_r) \left\{ \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + kn_m/\sqrt{\sigma} \right] /v_m + 2\omega N_{m,r} \right\} R_r \tag{19}$$

- $N_{m,r}$: number of cold boxes used for temperature range r at period m
- X_r : number of cold accumulators used for a temperature range r cold box
- $E(\Delta)$: expected distance from terminal to consignees
- $\overline{n}_m$: average number of consignees served by the same vehicle at period m
- n_m : number of consignees the carrier serves at period m
- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- σ : number of consignees per unit area
- v_m : road speed at period m
- ω : loading or unloading time for one cold box
- R_r : emissions from refrigerant leakage due to accumulating cold for a temperature range r accumulator per unit time

Furthermore, in Eq. (19), $N_{m,r}$, $\overline{n}_m$, n_m can be substituted by the right hand sides of Eq. (2), (6), (4), respectively. Therefore, Eq. (19) can be expressed through the decision variables, θ_{ijt}^m.

2.4 Constraints

For a delivery scheduling model, there exist some general constraints such as capacity limits of vehicles. In addition, this paper estimates vehicle routing time and distance using continuous approximation (Daganzo, 1999). The related equations for these issues are as follows.

2.4.1 Capacity limit of vehicles

In general, fleet size of a carrier is fixed. Total volume of all temperature ranges of cold boxes loaded in the same vehicle cannot exceed vehicle capacity. According to Hsu and Chen (2014), the constraint for vehicle capacity can be expressed as

$$a_m \leq \Omega, \quad \forall m \tag{20}$$

where

- a_m : number of vehicles used at period m
- Ω : fleet size

According to Eq. (3), a_m in Eq. (20) can be substituted by a function of shipping volume and the decision variables of the proposed model. Thus, Eq. (20) can be expressed through the decision variables, θ_{ijt}^m.

2.4.2 Estimation of vehicle routing time

This paper refers to Hsu and Chen (2014) to estimate vehicle routing time and distance using continuous approximation (Daganzo, 1999). Thus, average vehicle travel time from terminal to consignees at period m, ρ_m, can be computed as

$$\rho_m = \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + kn_m/\sqrt{\sigma} \right] /v_m \tag{21}$$

where

- $E(\Delta)$: expected distance from terminal to consignees

- k : constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
- $\overline{n}_m$: average number of consignees served by the same vehicle at period m
- σ : number of consignees per unit area
- v_m : road speed at period m

Eq. (21) can be substituted by a function of shipping volume and the decision variables of the proposed model. Therefore, Eq. (21) can be expressed through the decision variables, θ_{ijt}^m.

Finally, a mathematical programming model is formulated here to optimize the delivery schedule for multi-temperature food, based on the cost functions and constraints in Sections 3.3 and 3.4.

$$\min[C_{Inv} + C_{Tra} + C_{Ele} + C_{Pen} + T(G_{Oil} + G_{Ele} + G_{Ref})] \tag{22a}$$

$s.t.$

$$C_{Inv} = \sum_i \sum_j \sum_t q_{ijt} B_i (y_{ijt}^s - y_{ijt}^f) \tag{22b}$$

$$C_{Tra} = \sum_m \left\{ a_m f + \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] \tau_m o_m + \sum_r \delta N_{m,r} \right\} \tag{22c}$$

$$C_{Ene} = \sum_m \sum_r \left\{ \phi_r N_{m,r} \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] / v_m \right\} \tag{22d}$$

$$C_{Pen} = \sum_m \sum_i \sum_j \theta_{ijt} b_{ijt} q_{ijt} P_i h_i \left[\lambda (y_{ijt}^s + \rho_m - s_{ijt}) \right]^{\xi_i} \tag{22e}$$

$$G_{Oil} = \sum_m \left\{ \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] \tau_m o_m \alpha_{oil} \right\} \tag{22f}$$

$$G_{Ele} = \sum_m \sum_r (N_{m,r} X_r) \left\{ \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] / v_m + 2\omega N_{m,r} \right\} \gamma \alpha_{Ele} \tag{22g}$$

$$G_{Ref} = \sum_m \sum_r (N_{m,r} X_r) \left\{ \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] / v_m + 2\omega N_{m,r} \right\} R_r \tag{22h}$$

$$a_m \leq \Omega, \quad \forall m \tag{22i}$$

$$\rho_m = \left[\frac{2E(\triangle)\bar{n}_m}{n_m} + k n_m / \sqrt{\sigma} \right] / v_m \tag{22j}$$

$$Q_{m,r} = \sum_i \sum_j \sum_t \theta_{ijt} A_{i,r} q_{ijt} V_i \tag{22k}$$

$$N_{m,r} = Q_{m,r} / \beta \tag{22l}$$

$$a_m = e \sum_r N_{m,r} / \chi \tag{22m}$$

$$n_m = \sum_j \max(\theta_{ijt}, \forall i, t) \tag{22n}$$

$$D_m = Q_m / n_m \tag{22o}$$

$$\bar{n}_m = \chi / D_m \tag{22p}$$

Eq. (22a) represents the objective function that minimizes cost through the entire study duration. Eq. (22b), (22c), (22d), and (22e) express inventory, transportation, electric power, and penalty cost during the entire study duration, respectively. Eq. (22f), (22g), and (22h) estimate emissions from fuel, electric power consumption, and refrigerant leakage in the MTJD system, respectively. Eq. (22i) requires capacity limits for vehicles. Finally, Eq. (22j) expresses the estimation of vehicle travel time.

2.5 Algorithm

The solution for the proposed model contains departure time for each order. If the study duration is divided into l periods, and the carrier receives w orders. There are l^w feasible solutions. In practice, l^w is usually a huge number, and it is time-consuming to find an optimal solution. For a carrier who transports a lot of food orders with delivery time windows, the time for solving should be short. Otherwise, some delivery time windows might be violated because the carrier spends too much time on solving scheduling problem. For this reason, a heuristic algorithm is required. This paper follows Hsu et al. (2013) and Hsu and Chen (2014) to adopt Simulated Annealing algorithm to solve the proposed model and set the time for solving to be 0.5 hour. The optimal solution is output when the solving time runs out. Such solving time may not sufficient to find the optimal solution, but in practice, carriers cannot spend a lot of time to solve daily delivery problem. Otherwise, their operations may be delayed.

The values of the Simulated Annealing algorithm parameters include (1) the initial temperature $Z_0 = 50$; (2) the decreasing ratio of temperature is 0.8, and the stop temperature is 0.1; and (3) the number of moves at each temperature is 2000. Referring to Heragu and Alfa (1992) and Yan and Luo (1999), the SA algorithm can be described as follows.

Step 0. Find an initial solution, H, and calculate its objective function, $K(H)$. This paper chooses the lower limit of delivery time windows of each order to be combine the initial solution.

Step 1. At temperature Z_x, implement the Metropolis algorithm (Metropolis et al., 1953):

(1) Randomly choose an order and randomly generate a variable $\pi \sim (0, 1)$; if $\pi \geq 0.5$, $y^s_{ijt} = y^s_{ijt} + 1$; otherwise, $y^s_{ijt} = y^s_{ijt} - 1$. Let the altered solution be adjacent solution, H'. Calculate the objective value $K(H')$ for adjacent solution H'.

(2) Determine whether the new solution is accepted.

(2.1) Calculate the difference between the objective function of H and H', $\tau = K(H') - K(H)$.

(2.2) If $\tau < 0$, then $H = H'$; else randomly generate a variable $\pi \sim (0, 1)$. If $\exp(-\tau/Z_0) \geq \pi$, then $H = H'$; else go to Step1.

(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 $Z_{x+1} = 0.8Z_x$, and go to Step 1.

Step 3. Output the optimal distribution time for each temperature range food, H^*.

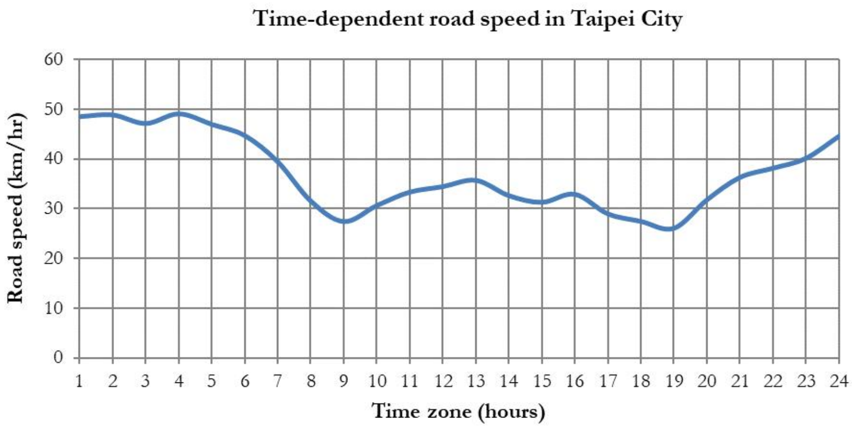
3. NUMERICAL EXAMPLE

This section presents a numerical example to demonstrate application of the model described in Section 3. Following W. Chen and Hsu (2015), this section assumes a 24-hour operating day as the entire study duration, which is divided into 24 periods. That is, the unit of time for this example is one hour. In this example, all parameters are the same as those in W. Chen and Hsu (2015). The carrier serves consignees located in an area of 500 square kilometers, and the time-dependent road speed in this area is shown in Figure 1. For parameters related to the object carrier, the lists of equipment and delivered goods are provided in Tables 1 and 2, respectively. As shown in Table 2, shipping goods in this example contain five temperature ranges of food. Furthermore, based on the density column, foods in Ranges 3 and 4 are heavy as compared with those in Ranges 1, 2, and 5. In this example, the carrier receives 1177 orders for 20 kinds of food from 85 different retailers, who are not only shippers but also consignees. Each order is consigned to a delivery time window. Figure 2 shows the time-dependent shipping demand during the entire study, in terms of weight (kg). The demand time is defined as the middle of a delivery time window. Shipping demand for most temperature range food peaks from 7:00-9:00 and 14:00-16:00. Moreover, Range 3 has the greatest demand, and Range 1 is most centralized (W. Chen & Hsu, 2015).

For carbon tax, the Chung-Hua Institution for Economic Research (2009) studied the Green Tax Reform through a project entrusted by Executive Yuan, Taiwan. They reviewed green tax regulations in different countries and suggested that Executive Yuan should set carbon tax rate as NT$750/tCO2e. We use this tax rate as the cost for unit carbon emission.

3.1 Cost structures under minimized cost

Table 3 lists the cost structures obtained with and without carbon tax. It is clear from the data that total cost obtained with carbon tax, NT$352,489, is lower than that obtained without carbon tax, NT$362,018. The main reason for this result is the difference in fuel and electric power costs between the two cases. The results show that carbon tax not only helps the carrier reduce the fuel cost from NT$122,285 to NT$108,915, but decreases the percentage that the fuel cost accounts for from 33.78% to 30.90% of the total cost. This further implies that carbon tax can lessen the effect of oil prices on carriers' operation costs since fuel cost dramatically varies with oil prices. As for electric power cost, the case with carbon tax results in NT$78,243, and is less than that obtained without carbon tax, NT$82,783. However, the proportions of electric power cost to total cost in the two cases, 22.20% and 22.85%, respectively, with



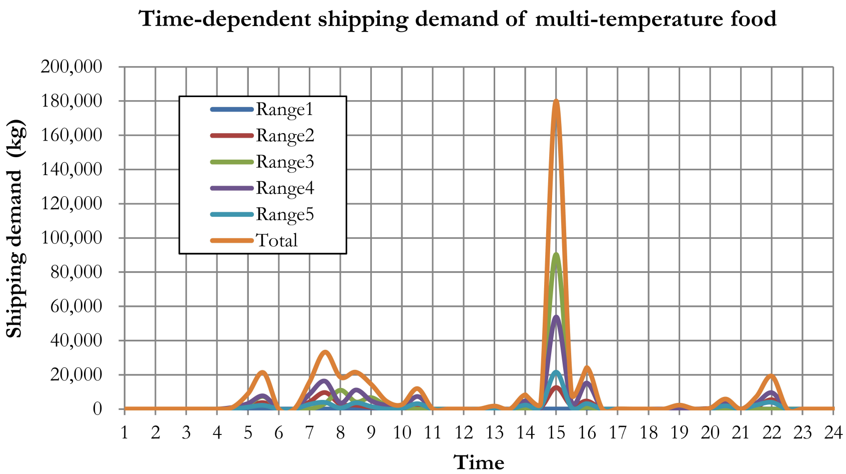
Source: Hsu and Chen (2014)

Figure 1: Time-dependent road speed in Taipei City.

Table 1: Value of parameters related to vehicles and refrigerants.

Definition	Value
Capacity of refrigerated and regular vehicle	16 m^3
Fuel consumption of regular vehicle	0.09434 Liters/km
Freezer capacity (in terms of cold accumulators)	78
Unloading time for a cold box	1 minute
Capacity of a cold box	300 Liters
Volume of a cold box	532 Liters
Number of cold accumulators used for a cold box (temperature range 1, 2, 3, 4, 5)	6, 6, 6, 4, 0
Refrigerant category and charge of freezer	R507, 3kg

Source: W. Chen and Hsu (2015)



Source: W. Chen and Hsu (2015)

Figure 2: Time-dependent demand for different temperature ranges of food.

and without carbon tax are close. The above comparisons imply that carbon tax does not raise carriers' costs but helps carriers reduce them because one more factor related to energy consumption, emission cost, is taken into account in the programming model. Thus, optimal delivery scheduling tends to increase energy efficiency. In this numerical example, the carrier has to spend NT$6,547 on carbon tax, which accounts for 1.86% of the total cost. Regarding warehousing cost, the two conditions generate similar results, NT$74,963 and NT$74,015 in the cases with and without carbon tax, respectively. Finally, both cases result in no penalty cost because all food can be delivered within the time windows. In sum, the above results imply that carbon tax decreases energy consumption of delivery activities, then both greenhouse gas emissions and carrier's costs are decreased.

Table 2: Initial values of delivered food.

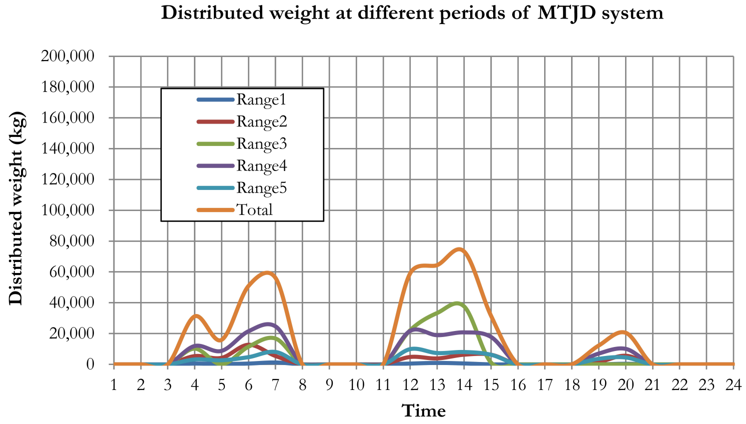
Temperature range	Food code	Food	Unit volume (L/item)	Unit weight (kg/item)	Density (kg/L)
Range 1 ($< 30°C$)	1	Sashimi	0.5	0.148	0.296
Range 2 ($-30°C \sim -18°C$)	2	Ice cream	1.2	0.480	0.400
	3	Frozen steamed buns with stuffing	1.5	0.512	0.341
	4	Frozen steamed dumplings	1.5	1.275	0.850
	5	Frozen vegetables	1.5	0.500	0.333
	6	Frozen meat	0.8	0.310	0.388
Range 3 ($-2°C \sim +2°C$)	7	Fish	0.5	0.478	0.956
	8	Duck	0.5	0.478	0.956
	9	Chicken	0.5	0.472	0.944
	10	Mutton	0.5	0.478	0.956
	11	Pork	0.5	0.172	0.344
	12	Beef	0.5	0.172	0.344
Range 4 ($0°C \sim +7°C$)	13	Ham	0.2	0.180	0.900
	14	Bean curd	0.2	0.300	1.500
	15	Milk	0.2	0.460	2.300
	16	Juice	1.8	1.800	1.000
	17	Vegetables	2	0.100	0.050
Range 5 ($+18°C \sim$)	18	Chocolate	0.3	0.132	0.440
	19	Cookie	1.2	0.170	0.142
	20	Soft dring	1.2	1.120	0.933

Table 3: Cost structure obtained with and without carbon tax.

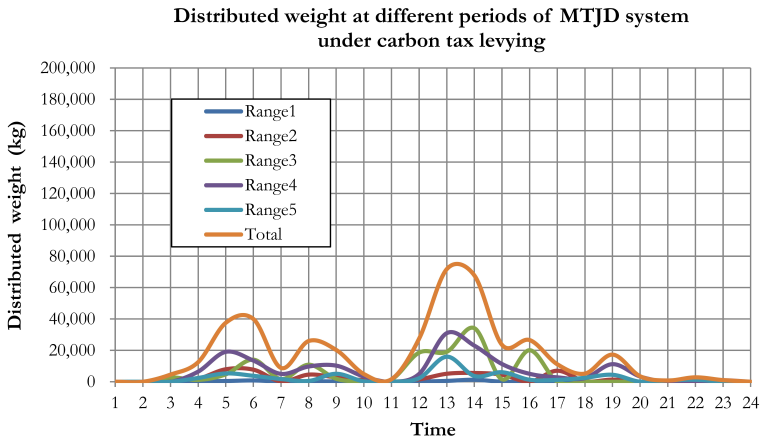
	Result obtained with carbon tax (NT$750/t$CO_2$e)		Result obtained without carbon tax	
Total cost (NT$)	352,489		362,018	
Transportation cost (NT$)	192,735	(54.68%)	205,265	(56.70%)
Vehicle cost (NT$)	22,000	(6.24%)	21,400	(5.91%)
Fuel cost (NT$)	108,915	(30.90%)	122,285	(33.78%)
Loading/unloading cost (NT$)	61,820	(17.54%)	61,580	(17.01%)
Warehousing cost (NT$)	74,963	(21.27%)	74,015	(20.45%)
Penalty cost (NT$)	0	(0.00%)	0	(0.00%)
Electric power cost (NT$)	78,243	(22.20%)	82,738	(22.85%)
Emission cost due to carbon tax (NT$)	6,547	(1.86%)		

3.2 Distributed weight under minimized cost

Figures 3 (a) and (b) show the time-dependent distributed weights for the optimal scheduling obtained without and with carbon tax, respectively. First, in the case without carbon tax, as discussed in W. Chen and Hsu (2015) and shown in Figure 3 (a), the time-dependent shipping demand can be smoothed by optimizing delivery scheduling for the MTJD system. Furthermore, the flexibility of the MTJD system helps carriers decrease distributed weights at higher traffic congestion periods if such adjustments do not cause late delivery. Thus, fuel consumption due to traffic congestion can be reduced (W. Chen & Hsu, 2015). Secondly, the results obtained with carbon tax, which are shown in Figure 3 (b), indicate that most of Range 1 food should be delivered at 13:00. Range 2 orders are mainly transported at 5:00, 6:00, 14:00 and 17:00. Distributed weight of Range 3 food peaks at 6:00, 8:00, 12:00, 13:00, 14:00 and 16:00, while that of Range 4 food tops at 5:00, 8:00, 9:00, 13:00 and 19:00. As for Range 5 food, it is chiefly dispatched at 5:00, 9:00, 13:00 and 15:00. The comparison of Figures 3 (a) and (b) shows that food belonging to the same temperature range should have more centralized delivery when the green tax is taken into account than the case without emission cost due to carbon tax. However, the results also show that delivery of certain temperature ranges should be mixed when carbon tax exists. There are some insights that can be found below by comparing distribution patterns for different temperature ranges, under conditions of the carbon tax.



(a) without carbon tax



(b) with carbon tax (NT$750/kgCO2e)

Figure 3: Time-dependent distributed volume.

First, for Ranges 3 and 4, it can be seen in Figure 3 (b) that their dispatched ranges cross. During the early periods, Ranges 3 and 4 are mainly distributed at 6:00 and 5:00, respectively. In the afternoon, the distributed weight of Range 3 peaks at 14:00 while Range 4 tops at 13:00. The reason for the cross is food density. Ranges 3 and 4 are both high-density food, as shown in Table 2. If they are transported simultaneously, vehicle payloads and fuel cost would dramatically increase. To disperse weights and decrease payload factors, optimal delivery scheduling determines they be dispatched separately. As for light food, Range 2 and Range 5 foods are also cross transported. Range 2 foods are usually delivered with Range 3 (at 6:00 and 14:00) while Range 5 foods are distributed with Range 4 (at 5:00 and 13:00). This suggests that carriers should distribute heavy goods with light ones to avoid transporting many groups of heavy cargos at the same time when they are levied carbon tax. As for the lowest temperature range, since the shipping weight of Range 1 is much lower than those of other ranges, the variation in Range 1 distribution patterns is insignificant when compared with that of other ranges.

When the optimized distributed pattern in Figure 3 (b) and road speed in Figure 1 are compared, it can be seen that distributed content is also related to road speed when carbon tax is taken into account. The results show that most of Range 4 food is distributed at periods with high road speed; that is, periods without traffic congestion. As shown in Figure 3 (b), more Range 4 foods are dispatched at 5:00 and 13:00 than those transported at 6:00 and 14:00, and the road speeds at 5:00 and 13:00 are higher than those at 6:00 and 14:00, as shown in Figure 1. On the contrary, more Range 3 food is delivered at 6:00 and 14:00 than that at 5:00 and 13:00. The reason for this is also the density of food.

Although both Range 3 and Range 4 foods are heavy when compared with other ranges, the densities of most Range 4 food are further higher than those of Range 3, as shown in Table 2. These observations imply that carriers should deliver high density food at periods without traffic congestion since heavy foods consume more energy than light ones. With high road speed, routing time and energy consumption can be reduced simultaneously. Thus, both delivery and emissions costs due to carbon tax decrease.

3.3 Emissions under minimized cost

Table 4 lists emissions obtained with the distributed pattern in Figure 3 (b). As shown in Table 4, emissions from fuel consumption account for most percentages of total emissions when carbon tax exists. The distribution pattern in Figure 3 (b) results in more emissions at 5:00-6:00 and 12:00-14:00 than those at other periods because distributed weights at these periods are high. Furthermore, emissions from fuel consumption at 12:00 are greater than at 14:00, but emissions from electric power consumption and refrigerant leakage at 12:00 are less than those at 14:00. The reasons for this are as follows. At 14:00, the distributed Range 3 food is more than that of Range 4, as shown in Figure 3 (b), and the temperature for storing Range 3 food is lower than that of Range 4. That is, Range 3 food consumes more electric power and refrigerant than Range 4 food. Therefore, the distribution pattern results in more emissions from electric power consumption and refrigerant leakage at 14:00. However, at 12:00, the distributed Range 3 food is less than that of Range 4, and the density of Range 4 is higher than that of Range 3, as shown in Table 2. That is, Range 4 food consumes more fuel than Range 3 food. Therefore, the distribution pattern results in more emissions from fuel at 12:00. However, since greenhouse gas from fuel accounts for the greatest percentage of total emissions in the MTJD system, total emissions at 12:00 are still greater than at 14:00. For greenhouse gas generated during the entire study duration, total emissions obtained with carbon tax, 8729.57kgCO2e, are markedly reduced when compared with that obtained without carbon tax, 9780.42 kgCO2e, which is calculated in W. Chen and Hsu (2015).

4. CONCLUSIONS

Since many governments around the world have planned carbon taxes for greenhouse gas emissions, optimizing delivery processes while considering the carbon tax is an important issue for multi-temperature food carriers. This paper aims to optimize delivery scheduling for multi-temperature food while simultaneously taking into account delivery and emissions costs due to carbon tax, time-dependent demand, and various traffic congestion issues. The results indicate that carbon tax can lessen the effect of fuel consumption on operation cost and both transportation cost and emissions can be reduced. The greenhouse gas from fuel consumption accounts for the great percentage of total emissions in the MTJD system. Furthermore, the results show that carriers should deliver high density middle temperature ranges food at periods without traffic congestion. Food belonging to the same temperature range should have more centralized distribution when carbon tax exists than the case without emission cost.

However, this paper limits time for solving the model to be 0.5 hour due to considering practice. Under this limitation, the solutions may be local optimal, not global optimal. Future studies may design heuristics to improve the solving efficiency and compare the global optimal solutions obtained without and with carbon tax, respectively. This paper assumes emissions due to back-haul of vehicles are equal to those of the delivery process. However, payload factors of vehicles change after unloading food. Future studies may expand the model and explore reverse logistics issues for the MTJD system. Furthermore, this paper focuses on emissions that depend on delivery scheduling. Future studies can expand the model to discuss emissions due to other activities in the whole multi-temperature food supply chain.

Table 4: Emissions from different sources at different periods when carbon tax is NT$750/tCO2e.

Time	Emissions (unit: kgCO2e)			
	Fuel Consumption	Electric Power consumption	Refrigerant Leakage	Total
1:00	0.00	0.00	0.00	0.00
2:00	0.00	0.00	0.00	0.00
3:00	0.00	0.00	0.00	0.00
4:00	4.76	0.17	0.01	4.94
5:00	1698.45	20.44	1.31	1720.20
6:00	1272.88	18.47	1.16	1292.51
7:00	176.50	3.96	0.26	180.72
8:00	453.39	9.88	0.63	463.90
9:00	265.78	5.55	0.36	271.69
10:00	48.85	1.75	0.12	50.72
11:00	11.47	0.83	0.05	12.35
12:00	1358.33	20.41	1.31	1380.05
13:00	1472.69	28.30	1.79	1502.78
14:00	1015.19	24.58	1.57	1041.34
15:00	401.48	5.98	0.41	407.87
16:00	34.04	0.85	0.07	34.96
17:00	139.99	7.10	0.45	147.54
18:00	11.70	0.21	0.01	11.92
19:00	36.14	1.98	0.13	38.25
20:00	163.62	3.95	0.26	167.83
21:00	0.00	0.00	0.00	0.00
22:00	0.00	0.00	0.00	0.00
23:00	0.00	0.00	0.00	0.00
24:00	0.00	0.00	0.00	0.00
Total	8565.26	154.41	9.9	8729.57

NOMENCLATURE

Symbol	Definition
$A_{i,r}$	Binary variable, if food i is stored at temperature range r, $A_{i,r} = 1$; otherwise, $A_{i,r} = 0$.
B_i	Warehousing cost of unit food i per unit time
$C_{delivery}$	Delivery cost due to carbon tax in the MTJD system
C_{Ene}	Electric power cost in the MTJD system
$C_{emission}$	Emission cost due to carbon tax in the MTJD system
C_{Inv}	Warehousing costs in the MTJD system,
C_{Pen}	Penalty cost in the MTJD system
C_{Tra}	Transportation cost in the MTJD system
D_m	Average shipping volume for each shipper at period m
$E(\Delta)$	Expected distance from terminal to consignees
G_{Ele}	Emissions from electric power consumption
G_{Oil}	Emissions from fuel consumption
G_{Ref}	Emissions from refrigerant leakage
H	Current solution n the Simulated Annealing algorithm
$N_{m,r}$	Number of cold boxes used for temperature range r at period m
$K(H)$	Objection value of the solution H
O	Cost per unit fuel consumption

P_i	Value of food i
$Q_{m,r}$	Total shipping volume of temperature range r food that carrier distributes at period m
R_r	Emissions from refrigerant leakage due to accumulating cold for a temperature range r accumulator per unit time
T	Carbon tax for unit emission
V_i	Volume of unit food i
Z_x	Temperature at the xth iteration in the Simulated Annealing algorithm
a_m	Number of vehicles used at period m
b_{ijt}	Binary variable, if food i ordered by consignee j at time t could not be delivered within soft time window, $b_{ijt} = 1$; otherwise, $b_{ijt} = 0$.
d_m	Total vehicle travel distance at period m
e	Volume of a cold box
f	Fixed cost for dispatching a vehicle
h_i	Ratio of penalty to value of food i for consignee j
k	Constant; $k \approx 0.57$ when distance is calculated by Euclidean Metric (straight-line distance between two points), and $k \approx 0.82$ if distance is computed as Manhattan Metric (sum of the absolute differences of two points' Cartesian coordinates)
l	Number of periods the study duration is divided
n_m	Number of consignees that carrier serves at period m
$\overline{n}_m$	Average number of consignees served by the same vehicle at period m
o_m	Fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m, which is road speed at period m
q_{ijt}	Amount of food i ordered by consignee j at time t
s_{ijt}	Upper bound of time window for food i ordered by consignee j at time t
v_m	Road speed at period m
w	Number of orders the carrier receives
y^f_{ijt}	Arrival time at terminal of food i ordered by consignee j at time t
y^s_{ijt}	Departure time from terminal for food i ordered by consignee j at time t
Γ_m	Average vehicle payload factor at period m that measures deviation of a vehicle's fuel consumption rate from an average value based on payload
X_r	Number of cold accumulators used for a temperature range r cold box
Ω	Fleet size
α_{Oil}	Emission factor of unit oil consumption
α_{Ele}	Emission factor of unit electric power consumption
β	Capacity of a cold box
γ	Electric power consumption per unit time for unit cold accumulator
δ	Loading/uploading cost for a cold box at period m
σ	Number of consignees per unit area
θ^m_{ijt}	Binary variable. If departure time from terminal for food i ordered by consignee j at time t is m, $\theta^m_{ijt} = 1$; otherwise, $\theta^m_{ijt} = 0$.
λ	A parameter that is set 0 for delay being less than one period; otherwise, $\lambda = 1$
ξ_i	A parameter of food i, $\xi_i > 1$
π	Random variable
ρ_m	Average vehicle travel time from terminal to consignees at period m
ϕ_r	Electric power cost for a temperature range r cold box per unit time
χ	Vehicle capacity
ω	Loading or unloading time for one cold box

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