國　立　交　通　大　學
運　輸　與　物　流　管　理　學　系

博　士　論　文

多溫層食品運輸排程與溫室氣體排放研究

The Study on Delivery Scheduling and Greenhouse Gas Emissions for Multi-Temperature Food Transportation

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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. On the other hand, sources of greenhouse gas (GHG) emissions related to food transportation include energy consumption and refrigerant leakage. HFCs and PFCs generated by refrigerant leakage markedly increase global warming potential (GWP), and many governments around the world have developed futures markets for emission allowances or levied carbon taxes. Given this, how to deliver multi-temperature food considering GHG emissions has become an important issue for carriers. This dissertation aims to analyze and optimize medium-term planning and short-term operation for multi-temperature food transportation. Moreover, this dissertation explores greenhouse gas emissions from multi-temperature food delivery. For medium-term planning, this dissertation optimizes fleet size for carriers considering time-dependent multi-temperature food demand. For short-term operations, this dissertation optimizes vehicle loads and departure times from the terminal for each order of multi-temperature food, taking into account the fleet size decided during medium-term planning. Furthermore, this dissertation formulates mathematical models to estimate emissions from and Multi-Temperature Joint Delivery (MTJD) and Traditional Multi-Vehicle Delivery (TMVD) systems for food under time-dependent demand and various levels of traffic congestion. The emissions of the two systems are analyzed and compared under conditions of minimized delivery cost. Finally, the optimal vehicle load of a multi-temperature joint delivery system is analyzed with carbon tax. A series of numerical examples illustrate 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. The results indicate that, as compared to the TMVD system, the MTJD system yields less total emissions by lowering fuel consumption even when it generates more CO_2e due to refrigerant leakage and electric power consumption for freezers. This dissertation suggests carriers use the MTJD system to reduce routing distances and emissions simultaneously. The results show that in the MTJD system, there exists economies of scale in the relationship between carbon footprints and distributed volume. However, in the TMVD system, the influence of distributed volume on average carbon footprints is not noticeable. For the delivery scheduling under carbon tax, the results suggest carrier delivers the food with high density at periods with high road speed and transport the food with low density at periods with low road speed. Thus, the delivery and emissions cost can be reduced simultaneously. The results show that carbon tax does not raise carriers' cost, even helps carrier reduce delivery cost because more influence related to energy consumption are taken into account.

Keywords: multi-temperature joint distribution; food transportation; time-dependent demand; fleet size; delivery scheduling; greenhouse gas emissions

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NOMENCLATURE

Symbol	Definition
ALR	annual refrigerant leakage rate of equipment
ALR^{MTJD}	annual refrigerant leakage rate of a freezer in the MTJD system
ALR_r^{TMVD}	annual refrigerant leakage rate of a range r vehicle in the TMVD system
B_i	warehousing cost of unit food i per unit time
C_{Ele}	electric power cost
C_{Pen}	penalty cost
C_{Tra}	transportation cost
C_{War}	warehousing cost
$\overline{D}_m$	average shipping volume for each shipper at period m in the MTJD system
$\overline{D}'_{m,r}$	average distributed volume of a range r vehicle for each shipper at period m in the TMVD system
$E(\Delta)$	expected distance from terminal to shippers' retailer stores
F_{ij}	cost of retailer j selling food i, excluding shipping charge
$G_{electricity}$	emissions from electric power consumption in the MTJD system
G_{Oil}	emissions from fuel consumption in the MTJD system
G'_{Oil}	emissions from fuel consumption in the TMVD system

$G_{refrigerant}$	emissions from refrigerant leakage in the MTJD system
$G'_{refrigerant}$	emissions from refrigerant leakage in the TMVD system
GWP	global warming potential of refrigerant used by equipment
GWP^{MTJD}	global warming potential of refrigerant in freezer in the MTJD system
GWP'^{TMVD}_{r}	global warming potential of refrigerant in a range r vehicle in the TMVD system
H	initial solution
H'	adjacent solution
H^*	optimal departure time from terminal for each order of multi-temperature range foods
I_m	number of idling vehicles at period m in the MTJD system
K_r	emissions from refrigerant leakage due to accumulating cold for a range r accumulator per unit time in the MTJD system
K'_r	emissions from refrigerant leakage per unit operating time of a range r vehicle in the TMVD system
K_{year}	annual emissions from refrigerant leakage of equipment
$\bar{L}_m$	average vehicle load at period m in the MTJD system
$\bar{L}'_{m,r}$	average load of a range r vehicle at period m in the TMVD system
M	refrigerant charge in equipment
M^{MTJD}	refrigerant charge of a freezer in the MTJD system
M_r^{TMVD}	refrigerant charge of a range r vehicle in the TMVD system

$N^1_{m,r}$ number of cold boxes used for temperature range r food at period m

$N^2_{m,r}$ number of cold cabinets used for temperature range r food at period m

$N'_{m,r}$ number of containers used for range r food at period m in the TMVD system

O fuel cost per unit routing distance

P_i value of food i

Q_{ijt} amount of food i ordered by retailer j at time t

R_{ij} minimal profit for selling food i, which is accepted by retailer j

S_{ijt} latest acceptable times for arrival of food i ordered by retailer j at time t

T_x temperature at xth move of the SA algorithm

T_0 initial temperature of the SA algorithm

U_{ijt} earliest acceptable times for arrival of food i ordered by retailer j at time t

V^1 capacity of a cold box

V^2 capacity of a cold cabinet

V'^1 volume of a cold box

V'^2 volume of a cold cabinet

V_i volume of unit food i

W_i weight of unit food i

$\overline{W}_r$ weight of a range r cold box with cold accumulators in the MTJD system

$\overline{W}'$ weight of a container in the TMVD system

X_r number of cold accumulators used for a range r cold box in the MTJD system

γ	cost for unit emission
a_m	number of vehicles used at period m in the MTJD system
$b_{ijt} = \begin{cases} 1 \\ 0 \end{cases}$	if food i ordered by retailer j at time t could not be delivered within soft time window; otherwise
c_1	holding cost per vehicle for the entire study duration per vehicle per period in the MTJD system
c_2	idling cost per vehicle per period in the MTJD system
d_{ij}	ratio of penalty to value of food i for retailer j
e	electric power consumption per unit time, unit cold accumulator
f	fixed cost for dispatching one vehicle in the MTJD system
g	freezer capacity in terms of cold accumulator
h	loading or unloading time for a cold box in the MTJD system
h'	loading or unloading time for a container in the TMVD system
k	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.
m_1	number of periods in an operating day
m_2	number of orders of food to different retailers in an operating day
n_m	number of shippers a carrier serves at period m in the MTJD system
$n'_{m,r}$	number of shippers the carrier serves at period m by range r vehicle in the TMVD system
$\bar{n}_m$	average number of shippers served by the same vehicle at period m in the MTJD system

$\bar{n}'_{m,r}$ average number of shippers served by the same range r vehicle at period m in the TMVD system

o_m fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m in the MTJD system

$o'_{m,r}$ fuel consumption rate (km/L) of a range r vehicle under average vehicle payload and speed v_m in the TMVD system

o'^{0}_{r} fuel consumption rate when the engine of a range r vehicle only drives the compressor of the refrigeration unit without moving

p_r shipping charge for unit volume of temperature range r food in the MTJD system

q_{ijt} amount of food i that carrier dispatches to retailer j at time y^{s}_{ijt}

u_{ijt} lower bounds of a soft time window for food i ordered by retailer j at time t

s_{ijt} upper bounds of a soft time window for food i ordered by retailer j at time t

v_m average vehicle speed at period m

y^{f}_{ijt} time that food i ordered by retailer j at time t arrives at terminal

y^{s}_{ijt} departure time from the terminal of food i ordered by retailer j at time t in the MTJD system

$Z(H)$ objective function

Γ_m average vehicle payload factor at period m that measure the deviation of a vehicle's fuel consumption rate from an average value based on payload in the MTJD system

$\Gamma'_{m,r}$ average vehicle payload factor of a range r vehicle at period m that measures the deviation of a range r vehicle's fuel consumption rate from an average value based on payload in the TMVD system

Δ difference between the objective function of H and H'

Φ average payload in the long run in the MTJD system

Φ'_r average payload for temperature range r vehicles in the long run of the TMVD system

Ω_m fleet size of vehicles of the MTJD system at period m

Ω^* optimal fleet size of the MTJD system

$\alpha_{electricity}$ emission factor of electric power consumption

α_{oil} emission factor of unit fuel

$\beta_m(\Omega)$ fraction of demand lost with a fleet size of Ω vehicles of the MTJD system at period m

γ^1 capacity utilizations of cold boxes

γ^2 capacity utilizations of cold cabinets

γ^3 capacity utilizations of vehicles

δ^1 loading/unloading costs for a cold box

δ^2 loading/unloading costs for a cold cabinet

ξ_i a parameter of food i, $\xi_i > 1$

η annual average operating time of a freezer in the MTJD system

η'_r annual average operating time of a range r vehicle in the TMVD system

$\theta_{ijt}^m = \begin{cases} 1 & \text{if departure time for food } i \text{ ordered by retailer } j \text{ at time } t \text{ is } m; \\ 0 & \text{otherwise} \end{cases}$

$\kappa_{ijt}^{m} = \begin{cases} 1, & \text{if food } i \text{ ordered by retailer } j \text{ at time } t \text{ is dispatched at period } m \text{ with range } r \text{ cold box in the MTJD system;} \\ 0, & \text{otherwise} \end{cases}$

$\kappa'^{m,r}_{ijt} = \begin{cases} 1, & \text{if food } i \text{ ordered by retailer } j \text{ at time } t \text{ is dispatched at period } m \text{ using a range } r \text{ vehicle in the TMVD system} \\ 0, & \text{otherwise} \end{cases}$

λ a parameter, which is set for the delay being less than one period

$\mu_{ijt}^{m} = \begin{cases} 1 & \text{if } U_{ijt} \leq m < S_{ijt},; \\ 0 & \text{otherwise} \end{cases}$

$\pi(\Omega)$ estimated profit function for the carrier for the entire study duration with fleet size Ω in the MTJD system

$\varpi_{i,r} = \begin{cases} 1 & \text{if food } i \text{ should be stored in temperature range } r; \\ 0 & \text{otherwise} \end{cases}$

ρ_m average vehicle travel time from terminal to retailers during period m in the MTJD system

σ number of shippers per unit area

τ_1 a random variable $\tau_1 \sim U(0,1)$; if $\tau_1 > 0.5$, $y_{ijt}^{s} = y_{ijt}^{s} + 1$; otherwise, $y_{ijt}^{s} = y_{ijt}^{s} - 1$.

τ_2 a random variable $\tau_2 \sim U(0,1)$. If $\exp(-\Delta / T_x) \geq \tau_2$, then $H = H'$; else go to Step1.

ϕ_r^1 electric power cost of a cold box for storing range r food per unit time

ϕ_r^2 electric power cost of a cold cabinet for storing range r food per unit time

χ vehicle capacity of the MTJD system

ψ_i estimated price of selling food i

$$\omega_{ijt} = \begin{cases} 1 & \text{if retailer } j \text{ consigns food } i \text{ to the carrier at time } t; \\ 0 & \text{otherwise} \end{cases}$$

Chapter 1 Introduction

The general field of interest in this disseration is multi-temperature joint delivery for food in response to time-dependent demand, various levels of traffic congestion and greenhouse gas emissions. This chapter presents an overview of the research background, motivation, research objectives, scope, and the framework of this dissertation.

1.1 Research background and motivations

In light of the demand for high-quality fresh food, transportation requirements for fresh food delivery have been continuously increasing in urban areas. Demand for temperature-controlled food is increasing in many markets across the globe; thus, the market for low-temperature logistics is expanding (Transport Intelligence, 2008). According to Ministry of Economic Affairs, Republic of China (2012), the output value for the low temperature food and logistics industry in Taiwan are NT$28,000 and NT$50,000 million, respectively. The leading firms for low temperature logistics include President Transnet, Taiwan Pelican Express, and Kerry TJ Logistics Company. All of the above-mentioned carriers provide multi-temperature logistics service. 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. 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.

Hsu and Liu (2011) reviewed the techniques for multi-temperature food transportation and compared that the major techniques, the Traditional Multi-Vehicle Delivery (TMVD) and Multi-Temperature Delivery (MTJD). Traditional Multi-Vehicle Delivery (TMVD) uses a single type of refrigerated vehicle to distribute cargos in one temperature range only. Refrigerated vehicles maintain the required temperature using a mechanical compression refrigeration unit driven by an engine. TMVD uses one type of refrigerated vehicle to distribute cargos in a single temperature range around a set-point, such as vehicles with temperatures set at–20° C, 0° C, or +12° C. For deliveries in an urban area that typically has many shippers and small shipments, delivery vehicles usually stop and open doors frequently. Once temperature-sensitive food is exposed to the outside atmosphere due to vehicle door opening, the temperature inside the vehicle is changed and bacteria grow quickly. Although the technique requires a large initial investment, it yields cost benefits due to economies of scale (Hsu and Liu, 2011). Compared with TMVD, the Multi-Temperature Joint Delivery (MTJD) technique can transport more than one temperature range of goods simultaneously in a single regular vehicle. In multi-compartment vehicles, the refrigerated space is subdivided into a number of compartments with individual temperature set-points to provide flexibility for business operations (Tassou et al., 2009). The Industrial Technology Research Institute of Taiwan (ITRI) developed a multi-temperature joint delivery (MTJD) system to distribute food of different temperature ranges in the same vehicle, which enables carriers to ship a variety of multi-temperature food simultaneously. The MTJD system developed by ITRI maintains temperatures by using replaceable cold accumulators (eutectic plates) in standard cold boxes or cabinets that are loaded into regular vehicles. It utilizes replaceable cold accumulators (eutectic plates) of different temperatures and sizes in standardized cold insulated boxes to maintain precise temperatures. Cold accumulators gather cold through freezers installed at terminals. The boxes with cold accumulators are used in regular vehicles, which enhance flexibility. In this way, the temperatures in the cold boxes would be influenced during door openings. Hence, the MTJD system can save energy and maintain food quality better than a traditional refrigerated fleet. In addition, with the MTJD technique, carriers can change the combination of temperature ranges in the vehicle easily. Multi-temperature food, therefore, can be kept fresh and jointly distributed during the entire transit process. Kerry TJ Logistics Company indicated that using MTJD system helped the company save NT$30,000,000 and NT$7,000,000 per year for oil consuming and vehicle purchasing, respectively (Wang, 2008). Furthermore, the company also indicated that high quality in temperature control by using the MTJD system helped them attract more orders, including Haagen-Dazs, the famous ice cream company.

Hsu and Liu (2011) defined multi-temperature logistics as encompassing all processes involving the movement and storage of cargos in an efficient and cost-saving manner, where optimal temperature control is necessary to maintain the cargo’s original value and quality. However, time-dependent delivery demands for multi-temperature food also result in huge differences in the required numbers of vehicles for different periods. Peak shipping demand for perishable food typically occurs three or four hours before lunch or dinner, during which time shippers can process and provide food to their customers. Using the same terminal departure time for all shippers without considering variations in cumulative quantities at each period may yield huge cost. Therefore, 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. Carriers’ decisions regarding a departure time from the terminal and shipping charges for each order of multi-temperature food affect their shipping costs and revenues. For these reasons, this dissertation constructs a mathematical programming model to solve the optimal fleet size, shipping charge, and departure time from the terminal for each order for multi-temperature food by maximizing the carrier's profit.

One of the key sectors addressed by the 1997 Kyoto Protocol (United Nations, 1997) is transportation. Road transport is the biggest producer of greenhouse gases (GHG) in the transport sector and the major contributor is road freight, which typically accounts for just under half of the road transport total (Chapman, 2007). Currently, there are over a million refrigerated road vehicles used to distribute refrigerated foods throughout the world (Billiard, 2005; Gac, 2002). GHG emissions from food transportation include emissions from energy consumption and refrigerant leakage into the environment, and the HFCs and PFCs generated by refrigerant leakage markedly increase global warming potential (GWP). Because many governments around the world are committed to reducing GHG emissions, and some have developed futures markets for emission allowances or have levied carbon taxes, delivering multi-temperature food with considering emissions cost has become an important issue for carriers. In Taiwan, the government has planned green tax reform to reduce GHG emissions, which is the main policy of the administration (Chung-Hua Institution for Economic Research, 2009). For this reason, carriers have to take into account emissions cost before the green tax is put into practice. Table 1-1 provides a comparison between the TMVD and MTJD technologies and shows that the sources of emissions for the two systems are different. The TMVD system includes emissions from fuel consumption and refrigerant leakage due to refrigerated vehicle routing and loading/unloading time. However, the emissions from fuel consumption for the MTJD system depend on regular vehicle routing, but not on loading/unloading time. In addition, in the MTJD system, there are emissions from refrigerant leakage and electric power consumption by freezers installed at terminals. Although the TMVD and MTJD systems play important roles in multi-temperature food delivering and GHG emissions, few studies explore and compare them in an integrated analytical way.

Table 1- 1 Comparison of TMVD and MTJD technologies

Technique type	TMVD system	MTJD system
Technique characteristics[1]	Distributed separately using various temperature vehicles	Distributed jointly using regular vehicles and cold boxes
Vehicle equipment[1]	Refrigerated vehicles for low temperature range and regular vehicles for constant temperature food	Regular vehicles with cold accumulators and insulated boxes
Freezing system[1]	Conventional diesel engines driven vapor compression refrigeration systems inside vehicles	Freezers at terminal
Sources of emissions[2]	(1) Fuel consumption of refrigerated and regular vehicles (2) Refrigerant leakage from refrigeration systems inside vehicles	(1) Fuel consumption of regular vehicles (2) Electric power consumption of freezers at terminal (3) Refrigerant leakage from freezers at terminal

Sources: [1]Hsu and Liu (2011); [2]Kuo et al. (2010).

This dissertation aims to analyze the medium-term planning and short-term operations for multi-temperature food transportation. In this dissertation, the decision maker is a carrier, a logistics contractor who delivers food ordered by general retailers. The carrier has a terminal for temporary food storage and owns vehicles and temperature control equipment. On the other hand, shippers in this dissertation are general retailers in urban areas that sell fresh food to customers. Therefore, in this dissertation, the consignee is the retailers of multi-temperature food in urban area. Food delivery time and shipping charges influence the shippers' profits and willingness to consign.

In the medium-term planning, the carrier determines the optimal fleet size, taking into time-dependent shipping demand for multi-temperature food. In practice, the medium-term planning results should be revised seasonally or yearly. Under the optimal fleet size, the carrier makes decisions for the short-term operations; that is, the daily delivery scheduling for multi-temperature food. With the delivery scheduling results, the emissions from the delivery process can be estimated. This dissertation constructs mathematical programming models to solve the optimal fleet size, and shipping charges for the medium-term planning. Then, this dissertation optimizes the departure time from the terminal for each order for multi-temperature food for the short-term operations, by maximizing the carrier's profit. Furthermore, this dissertation formulates models for exploring the relationships between the carrier's operations and greenhouse gas emissions due to transporting multi-temperature food.

1.2 Research objectives

Based on the above-mentioned background, this dissertation aims to provide a support tool for carriers in fleet size, delivery scheduling, and strategy to confront green tax for multi-temperature food. The overall goal of this dissertation is to develop a better understanding of the multi-temperature food transportation system and to make contributions in improving the performance of the system. Specifically, the purpose of this dissertation is to study the planning, operations and environment problems for urban multi-temperature food carrier, as they capture the influence of time-dependent demand and various levels of traffic congestion. In view of this, this dissertation formulates a series of models. According to the issues of significance, which can be addressed as fleet size and delivery scheduling under demand-supply interaction, emissions under minimized cost, and delivery scheduling under emissions tax.

Specifically, the objectives and contributions of this dissertation are as follows.

(1) This dissertation investigates the carrier's medium-term planning and short-term operations for jointly delivering multi-temperature food. For the medium-term planning, this dissertation formulates models to help the carrier determine optimal fleet size, taking into account time-dependent shipping demand, carrier's revenue, penalty, and costs related to vehicles. Then, the short-term operations is constrained by the results of in medium-term planning. In the short-term operations, this dissertation explores demand-supply interaction and constructs a model to optimize departure times from the terminal for each order, by maximizing the carrier's profits.

(2) This dissertation formulates mathematical models to estimate and compare emissions from the MTJD and TMVD systems under time-dependent demand and various levels of traffic congestion. This dissertation analyzes the relationships among distributed food volume and characteristics, traffic condition, and dynamic emissions from different sources of the two systems. Moreover, this dissertation analyzes the carbon footprints of multi-temperature food in the two systems.

(3) This dissertation optimizes the optimal vehicle load of a multi-temperature joint delivery system when the cost for greenhouse gas emissions tax are taken into account. This dissertation analyzes the optimal delivery schedule, carrier's cost, and carbon footprints under carbon tax simultaneously.

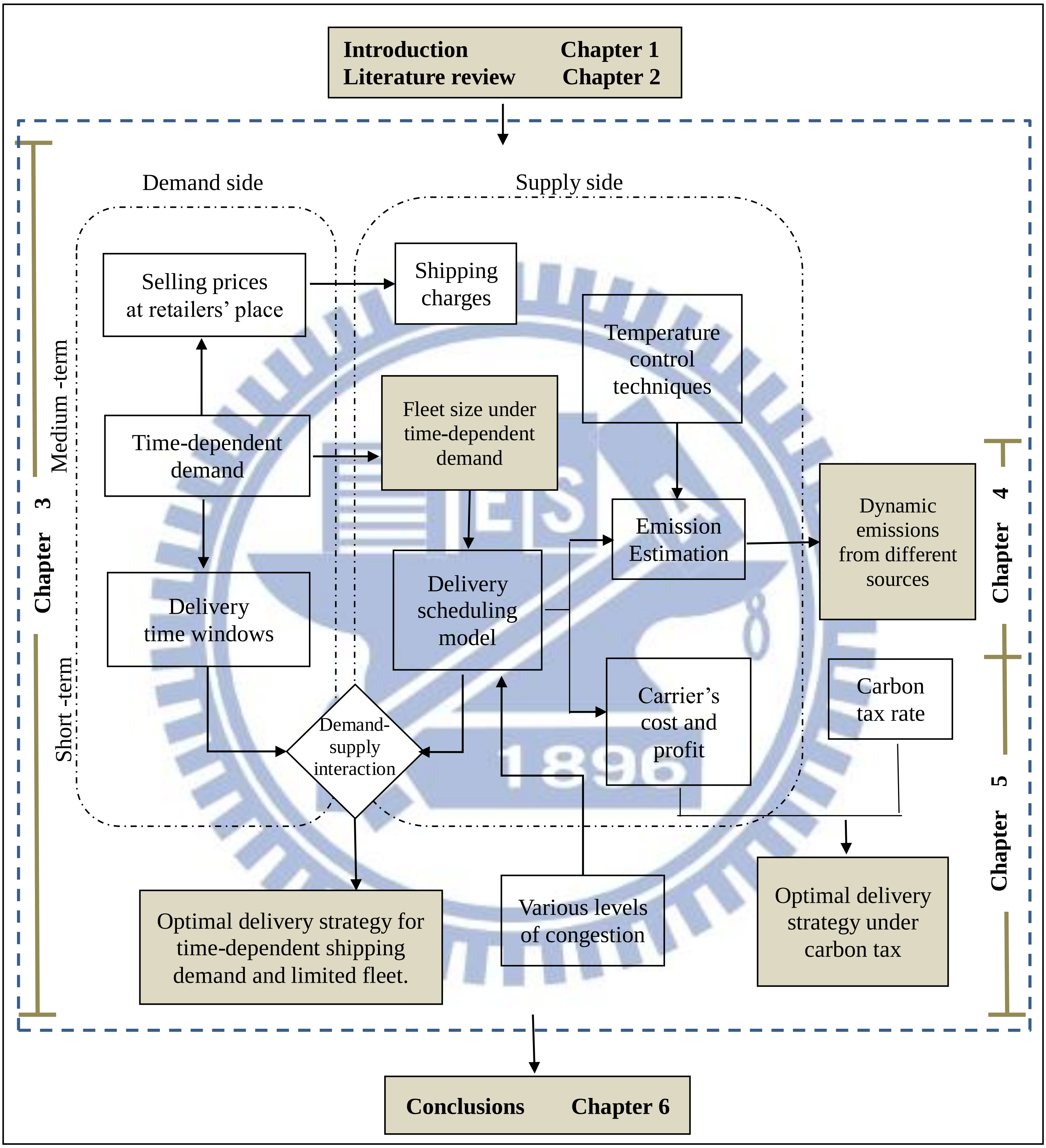
1.3 Research scope and framework

This dissertation analyzes the problem by formulating a series of mathematical models under the assumption that a carrier seeks to maximize profit. As discussed earlier, in this dissertation, the decision maker is a carrier, and the carrier has to make decisions for medium-term planning and short-term operations, respectively. The medium-term planning focuses on the fleet size and shipping charges. These two variables affect carrier's delivery service level and shippers' willingness to consign. The short-term operations focus on the variables which affect delivery scheduling. For the vehicle routing problem, this dissertation does not explore the delivery sequence of the same vehicle at each period, we only optimize the scheduling for the entire study duration, that is, vehicle load at each period. Moreover, the competition between carriers is not explored in this dissertation.

The framework of this dissertation is shown in Figure 1-1, which depicts the content of each considered factor in this dissertation. This dissertation contains three pats. In the first part, this dissertation analyzes the influence of shipping charges and delivery time on shippers' demand, carrier's fleet size and delivery scheduling for multi-temperature food transportation. As shown in Figure 1-1, the first part can be further divided into medium-term planning part and short-term operations part. The medium-term planning model determines the carrier's optimal fleet size and shipping charges for delivering different temperature ranges food under the objective of maximizing carrier's profit. The time-dependent shipping demand and vehicle holding cost are taken into account. In practice, the results of medium-term planning should be revised seasonally or yearly. In the short-term part, the daily operations, this dissertation deals with the delivery scheduling problem. This dissertation optimizes vehicle loads and departure times from the terminal for each order of food under demand-supply interactions between the carrier and shippers, taking into account the fleet size and shipping charges decided by medium-term planning. A mathematical programming model is formulated for determining the optimal delivery scheduling by maximizing profit for the carrier. This dissertation deals with dynamic and time-sensitive multi-temperature shipping demand and investigates how delivery scheduling affects shippers' willingness to consign. The costs considered into delivery scheduling model include transportation cost, electric power cost, warehousing cost, and penalty cost. These costs are affected by not only shipping volume but traffic condition. The higher the road speed, the lower the energy consumption rate for unit routing distance, and the less the vehicle travel time, which influences the penalty cost due to late delivery.

The second part of this dissertation devises an emissions estimation method for multi-temperature food delivery based on the results under optimized delivery scheduling. This dissertation assumes the energy consumption and refrigerant leakage are the basic criterions for estimating the greenhouse gas emissions in a multi-temperature food transportation system. The emissions from energy consumption depend on vehicle speed, routing distance, vehicle payload, and food storage temperature. The emissions from refrigerant leakage depends on temperature and vehicle routing time. This dissertation develops mathematical functions to estimate the emissions from the above-mentioned sources when the carrier uses the MTJD and TMVD system, respectively. This dissertation further compares the emissions from different sources and carbon footprints in the MTJD and TMVD system.

The third part of this dissertation assumes the carrier is levied carbon tax and has to determine delivery scheduling under minimized cost. The cost due to carbon tax levying depends on the emissions and carbon tax rate. Therefore, the third part of this dissertation combines the cost functions in the first part and the emissions estimation functions in the second part with a carbon tax rate. Then, a mathematical model for optimizing delivery scheduling is formulated. Furthermore, this dissertation analyzes the relationship between time-dependent demand, delivery cost, emissions, and carbon tax for the MTJD system.



Source: This dissertation.

Figure 1- 1 The framework of the dissertation

Figure 1-2 describes the research process, and the steps in detail are as follows.

(1) Define the research problems

Based on the background and motivation, this dissertation identifies the research problems, issues, scope, and objectives.

(2) Literature review

To better understand the problems, this dissertation reviews the existing literature in the relevant topics of optimal delivery scheduling and emissions estimation of multi-temperature food transportation.

(3) Fleet size optimization model

For medium-term planning, this dissertation formulates the model for optimizing fleet size, taking into account relevant costs and time-dependent demand

(4) Delivery scheduling model

For short-term operations, this dissertation formulates the delivery cost and profit functions of the MTJD system and constructs a model for determining departure time of each order of multi-temperature food.

(5) Shippers' choices model

This dissertation analyzes the factors which affect shippers' willingness to consign food. A model to describe and estimate retailers' shipping demand is formulated.

(6) Demand-supply interaction analysis

This dissertation analyzes the demand-supply interaction by integrating the delivery scheduling and shippers' choice models, using an algorithm to solve the problem.

(7) Emissions estimation model

This dissertation further discusses the environment impact of temperature-controlled food delivery. Mathematical models for estimating emissions from the MTJD and TMVD systems are formulated, taking into account time-dependent delivery volume and various levels of traffic congestion.

(8) Exploring delivery scheduling under carbon tax

Based on the delivery scheduling and emissions estimation model of the MTJD system, this dissertation formulates a model to optimize delivery scheduling when the carrier is levied carbon tax.

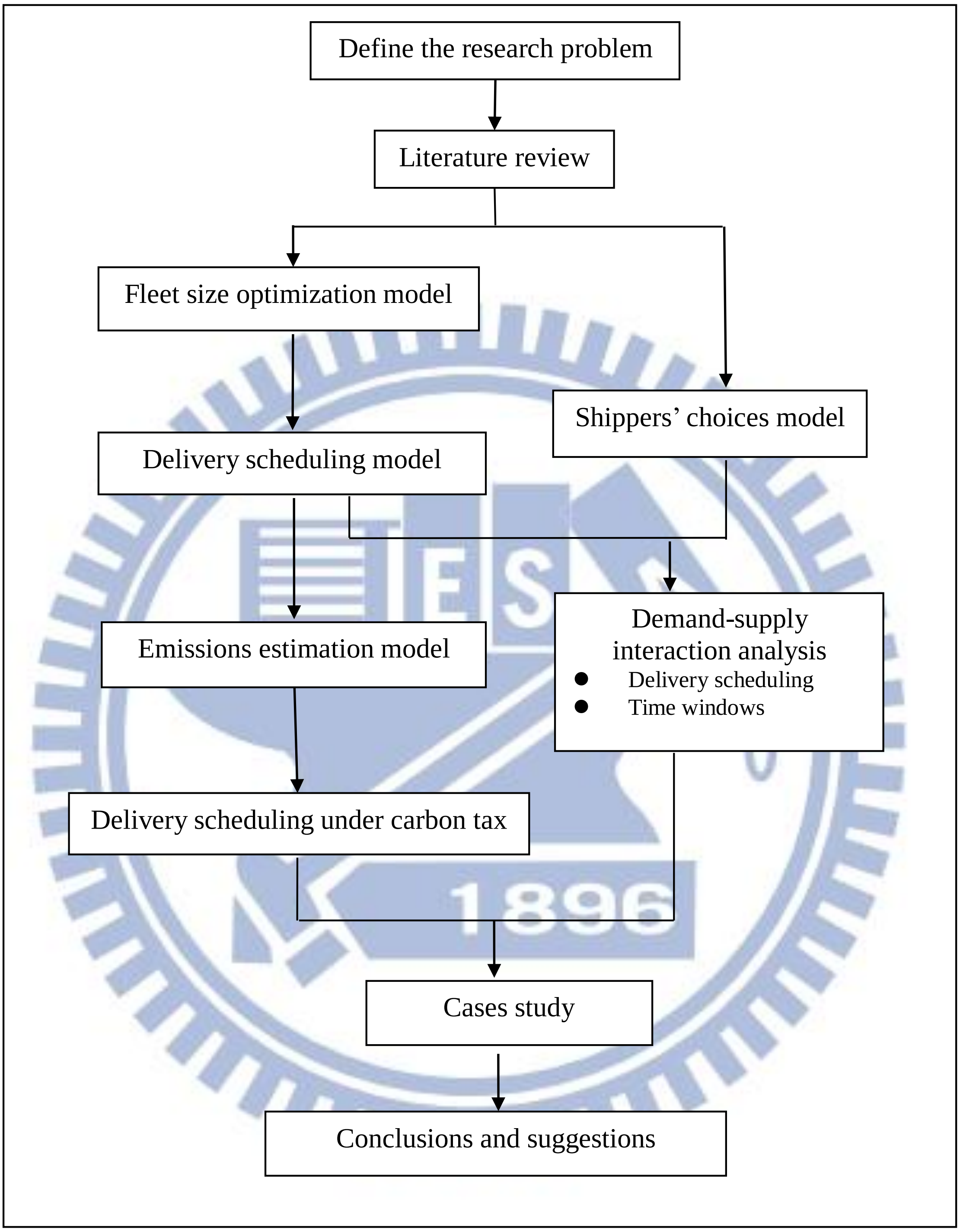
(9) Cases study

Numerical examples are provided in each part of this dissertation to illustrate the application of the proposed models.

(10) Conclusion and suggestions

The conclusion and suggestions for future studies of this dissertation are summarized.

The reminder of this dissertation is organized as follows. Chapter 2 reviews the literature on supply chain management and environment impact of temperature-controlled food. Chapter 3 describes the model formulation and case study for fleet size optimization and delivery scheduling. Chapter 4 presents the model formulation of GHG emissions estimations for the MTJD and TMVD system, with a numerical example. Chapter 5 presents a delivery scheduling model combining delivery and emissions costs, with a case study. Finally, the conclusions and suggestions for the future studies are summarized in Chapter 6.



Source: This dissertation.

Figure 1- 2 The research process flowchart

Chapter 2 Literature review

This dissertation aims to explore the fleet size, delivery scheduling problem, and emissions estimation of multi-temperature food transportation. Furthermore, major subjects related to multi-temperature food distribution include perishable food inventory, transportation network, temperature control techniques, environment impact, and sustainability of the perishable food supply chain. Therefore, this chapter reviews the literatures of fleet size optimization, delivery scheduling, emissions estimation, inventory, transportation network, environment impact, and sustainability of temperature-controlled food delivery as follows.

2.1 Fleet size optimization

Previous studies developed many fleet size optimization models to maximize carriers' operating profits. Turnquist and Jordan (1986) formulated a model for sizing a fleet of containers used to ship parts from a single manufacturing plant to a group of assembly plants. Beaujon and Turnquist (1991) formulated a model to optimize fleet sizing and utilizing simultaneously under dynamic and uncertain conditions, using network approximation approach. Du and Hall (1997) studied fleet sizing and empty equipment redistribution and developed decentralized stock control policies for empty equipment.

Bojovic (2002) developed an optimal control model to determine the number of rail freight cars to satisfy the demand and minimize the total cost. Godfrey and Powell (2002) studied the fleet management and resource allocation problems with an adaptive dynamic programming algorithm. Experimental work demonstrated that the modified algorithm works on problems with multi-period travel times. Furthermore, Godfrey and

Powell (2003) extended the previous study by nonlinear functional approximations that give the value of resources in the future. Wu et al. (2005) addressed a fleet-sizing problem in the context of the truck-rental industry. They developed a two-phase solution approach to solve large-scale instances of the problem. Phase I allocated customer demand among assets with a demand-shifting algorithm assuring feasibility in each sub-problem. Phase II used the initial bounds and dual variables from Phase I and further improves the solution convergence by Lagrangian relaxation. King and Topaloglu (2007) presented a model to coordinate the pricing and fleet management decisions of a freight carrier, considering a setting where the loads faced by the carrier over a certain time horizon are deterministic functions of the prices. Papier and Thonemann (2008) constructed an analytical models for fleet optimization and described the rental process as a queuing loss system. Moreover, they developed a profit function and derive several structural results, including the concavity of the profit function in the fleet size.

Summary: Although many studies explored the fleet size optimization problem for dynamic demand, most researchers focused on the relationship between inventory control, resource allocation, queuing, and fleet management. Few studies investigates the fleet size problem for multi-temperature food delivery that is time-varying during one operating day.

2.2 Delivery scheduling

There has been lots of researchers study delivery scheduling problem. Xue et al., (2001) developed an optimal scheduling approach for coordinating product delivery activities using fuzzy mathematics. In this approach, optimal delivery scheduling was carried out at three different levels, for situations involving one driver and one load, one driver and multiple loads, and multiple drivers and multiple loads. Garcia et al., (2004, 2005) dealt with the scheduling of orders and vehicle assignment for production and distribution planning in a scenario of no-wait, immediate delivery to the customer site. Yan et al. (2005) developed a short-term flight scheduling model for air express carriers to determine suitable routes and flight schedules with the objective of minimizing operating costs, subject to related operating constraints.

Torabi et al. (2006) investigated the lot and delivery scheduling problem in a simple supply chain consisting of a single supplier and multiple components on a flexible flow line. Li et al. (2008) studied the air transportation allocation problem and an assembly scheduling problem by formulating an integer linear programming problem with the objective of minimizing transportation cost and delivery earliness tardiness penalties. Pundoor and Chen (2009) studied an integrated production and distribution scheduling model in a two-stage supply chain consisting of one or more suppliers, a warehouse, and a customer. The problem fund a cyclic delivery schedule from the warehouse to the customer. Zegordi and Beheshti Nia (2009) considered the integration of production and transportation scheduling in a two stage supply chain environment. The objective function minimized the total tardiness and total deviations of assigned work loads of suppliers from their quotas.

Osman and Demirli (2012) studied the economic lot and delivery scheduling problem for a multi-stage supply chain comprising multiple items, with a novel formulation based on the quadratic assignment representation. Yan et al. (2012) developed a new concept of similarity of time and space for routing and scheduling to help security carriers formulate more flexible routing and scheduling strategies. Jin et al. (2013) quoted different delivery times in a supply chain consisting of a firm and a set of customer groups to maximize the profit.

Summary: The existing studies related to delivery scheduling explores the problem of single or multi-stages supply chain, various customers, with view of time-dependence and vehicle routing. But few studies focus on the scheduling for multi-temperature joint delivery, fleet size, time-windows, and environment impact simultaneously.

2.3 Emissions Estimation for transportation

For research related to emissions from cargo transportation, Pishvaee et al. (2012) proposed a bi-objective credibility-based fuzzy mathematical programming model for designing the strategic configuration of a green logistics network under uncertain conditions. Soysal et al (2013) developed a multi-objective model for a generic beef logistics network problem. The objectives of the model were minimizing total logistics cost and minimizing total amount of greenhouse gas emissions from transportation operations. Ozen and Tuydes-Yaman (2013) presented emission estimations in Turkey for the period of 2000-2009 by the characteristics of road freight movements. Chen et al. (2013) proposed a methodology to optimize truck arrival patterns to reduce emissions from idling truck engines at marine container terminals. Based on the waiting time, truck idling emissions were estimated. Pan et al. (2013) computed CO_2 emissions for two transport modes, road and rail, by real data from two main French retail chains and an optimization model. The emissions functions of the two modes were both piecewise linear and discontinuous functions.

Lin et al. (2014) presented an extensive literature review of Green Vehicle Routing Problems (GVRP). They categorized GVRP into Green-VRP, Pollution Routing Problem, VRP in Reverse Logistics, and suggested research gaps between its state and richer models describing the complexity in real-world cases. Demir et al. (2014) provided a review of recent research on green road freight transportation. They reviewed studies for freight transportation vehicle emission models and routing problems with fuel consumption components.

Summary: The above-mentioned studies explored emissions estimation for cargo transportation, but most of them focused on vehicle routing problem or energy efficiency, with real traffic data. Few studies estimated greenhouse gas emissions from the view of delivery scheduling or discussed the estimation methods with multi-temperature joint delivery issue. On the other hand, although many studies explored the emissions from refrigerant leakage, for low temperature logistics, few of them estimated the emissions due to refrigeration in a multi-temperature food delivery system. Moreover, most of above-mentioned studies used multi-objectives programming and set logistics cost and emissions as two different objectives. Few studies considered carbon tax. To fit this gap, this dissertation estimates the emissions from energy consumption and refrigerant leakage in the MTJD system, from the view of carrier's delivery scheduling. Thus, the influence of delivery scheduling on the emissions from different sources can be analyzed. Furthermore, this dissertation optimizes the delivery scheduling for the condition that the carrier is levied carbon tax.

2.4 Perishable food inventory

For research related to perishable inventory, Ghare and Schrade (1963) formulated a nonlinear model to solve the inventory problem for fresh food by assuming the decay rate as a constant. Covert and Philip (1973) extended Ghare and Schrade's model but set the decay rate as a Weibull distribution to construct an economic order quantity (EOQ) model, which became the foundation for follow-up research (e. g., Charkrabarty et al. (1998); Giri and Chaudhuri (1998); Hargia (1996)). Raafat (1991) reviewed all of the continuously deteriorating inventory models. In addition, in recent years, there have been many studies focused on the phenomenon of quality and shelf life decay over time. Bogataj et al. (2005) analyzed the importance of assuring the stability of cold chains in cold chain management (CCM). Likar and Jevsnik (2006) analyzed a survey related to the situation of cold chain maintenance in the food trade in Ljubljana.

Summary: Many studies related to perishable inventory discussed the decay rate and quality of food, but few studies explored perishable food issues from the view of multi-temperature joint delivery.

2.5 Transportation network for perishable food

In the line of research regarding transportation networks for perishable goods, Panozzo et al. (1999) analyzed situations and future trends for transport and distribution of food. They indicated that energy and environmental benefits could be obtained by optimizing the logistics chain, and multi-temperature vehicles and mini-containers could solve certain specific problems. Tarantilis and Kiranoudis (2001) studied the fresh milk distribution problem, and presented a new meta-heuristic (i.e., the backtracking adaptive threshold accepting algorithm) for solving the heterogeneous fixed fleet vehicle routing problem (HFFVRP). Zhang et al. (2003) presented a tabu search algorithm to optimize the structure of cold chains for distribution of chilled or frozen food. The physical distribution system was structured in such a way that the cost for storage and transportation in the whole distribution system was minimized, while the product quality requirement was fulfilled.

Hsu et al. (2007) extended the vehicle routing problem with time windows (VRPTW) by considering the randomness of the perishable food delivery process. They 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 (2008) developed an algorithm for the distribution of fresh vegetables in which the perishability represents a critical factor. They 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). The travel-times between two locations depended on both the distance and on the time of day. Chen et al. (2009) proposed a nonlinear mathematical model to consider production scheduling and vehicle routing with time windows for perishable food products in the same framework. The optimal production quantities, the time to start producing, and the vehicle routes can be determined in the model simultaneously.

Kuo and Chen (2010) presented an MTJD-based service model and a case study based on the requirements of the food chain and the operations of third-party logistics in Taiwan. Furthermore, they pointed out a way of using the MTJD model in which carriers could markedly reduce the logistical costs of handling frequent deliveries in small lots using less than truckload transportation, while maintaining customer satisfaction. Hsu and Liu (2011) compared conventional temperature control technologies for logistics with new ones, and 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 network.

Summary: Although many researchers explored the transportation network for perishable food, and some of them discussed the food stored in different temperature ranges, most of them focused on the network or vehicle routing problem without considering the demand-supply interaction between shippers and carrier.

2.6 Environmental impact of food supply chains

Over the past decade, many studies addressed the environmental impact of food supply chains. Sonesson and Berlin (2003) analyzed the environmental impact of milk supply chains based on lifecycle assessment. Mintcheva (2005) explained the specifics of food chain development and their corresponding environmental impact, and discussed the necessity of designing a policy mix of different types of measures. Coley et al. (2009) provided critical commentary on the conceptualization of food miles, followed by an empirical application of food miles to two contrasting food distribution systems based on the accounting of carbon emissions within these systems. Ma et al. (2010) presented an inventory analysis of carbon emissions for every food cycle phase and provided an assessment framework for food lifecycle carbon emissions. Pathak et al. (2010) calculated carbon footprints of Indian food consumption, analyzed differences in GHG emissions from vegetarian and non-vegetarian foods, and estimated GHG emissions at current and projected levels of food consumption in India. Gössling et al. (2011) reviewed the carbon intensity of selected foods and indicated the need for further research to refine and extend our understanding of the contribution that food management can make to reduce tourism’s carbon ‘foodprint’.

Summary: The above-mentioned research explored the environment impact due to food supply chain, by views of life cycle or calculating carbon footprints of food. However, few studies investigated the issue from the view of multi-temperature joint delivery system.

2.7 Sustainability of cold-chains

In recent years, researchers further explored the environmental impact and sustainability of cold-chains by taking into account emissions from refrigerant in temperature-control equipment. Vanek and Sun (2008) applied an energy consumption model to temperature-controlled food products distributed using surface transportation. They indicated the use of railroads can reduce lifecycle energy consumption as compared to using trucks. The increase in perishability of food products can undercut the energy savings and, in some circumstances, the use of intermodal rail can be environmentally superior to carload freight for delivery. Tassou et al. (2009) provided a review of current approaches to food refrigeration during road transport, estimates of their environmental impact, and research on the development and application of alternative technologies to vapor compression refrigeration systems. James and James (2010) addressed the likely effect of climate change on the cold-chain, using available literature. In addition to the generation of CO_2. They reviewed the use of alternative refrigerants and refrigeration cycles with a reduced potential for global warming. Zanoni and Zavanella (2011) presented a model for a food supply chain that encompasses the influence of both temperature and storage time, thus appreciating their impact on product quality, costs, and sustainability of the chain as related to quality degradation and energy consumption.

Summary: Although many studies indicated the importance of refrigerant leakage for greenhouse gas emissions, few studies explored the relationship between carriers' operations and emissions due to refrigerant leakage in a transportation system, by formulating mathematical model. On other hand, most of the past studies only discussed the low-temperature logistics and considered different temperature ranges simultaneously.

2.8 Summary

In sum, the existing studies regarding fleet size and delivery scheduling do not discuss these problems for multi-temperature food transportation. Although many researchers have discussed the importance of food temperature control during the transit process, except for Kuo and Chen (2010) and Hsu and Liu (2011) there is little research that addresses the application of the MTJD technique. Furthermore, Kuo and Chen (2010) focused on the framework for a cold chain using MTJD but 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 (2011) focused on the relationship between techniques choosing and handling volume for multi-temperature logistics in a hierarchical hub and spoke network but did not discuss time-dependent demand or demand-supply interaction between the carrier and shippers. Although the above-mentioned researchers discussed environmental impacts of food chains, little research simultaneously explored temperature-control techniques, carrier operations, and emission estimations of food logistics systems.

To fill the gap, this dissertation focuses on analyzing a joint delivery system by considering the costs of carriers and acceptable shipping charges with a time-dependent demand pattern. Moreover, this dissertation formulates mathematical models to estimate GHG emissions of both the MTJD and TMVD systems. Furthermore, this dissertation analyzes and compares the emissions from different sources in these two systems under minimized delivery costs, and explores the optimal delivery scheduling when the carrier is levied carbon tax.

Chapter 3 Optimizing fleet size and delivery scheduling for multi-temperature food delivery system

This chapter presents the model formulation of fleet size optimization, delivery scheduling optimization under demand-supply interactions, and an algorithm to solve the problem. The reminder of this chapter is organized as follows. Section 3.1 describes the studied problem and assumptions of this chapter. Section 3.2 describes the model formulation for fleet size optimization, and the optimal departure time programming model under optimized fleet size and demand-supply interaction. The algorithm and a numerical example are provided in Section 3.3 and Section 3.4 to illustrate the application of the model, respectively. Finally, Section 3.5 provides the summary of this chapter.

3.1 Introduction to the problem

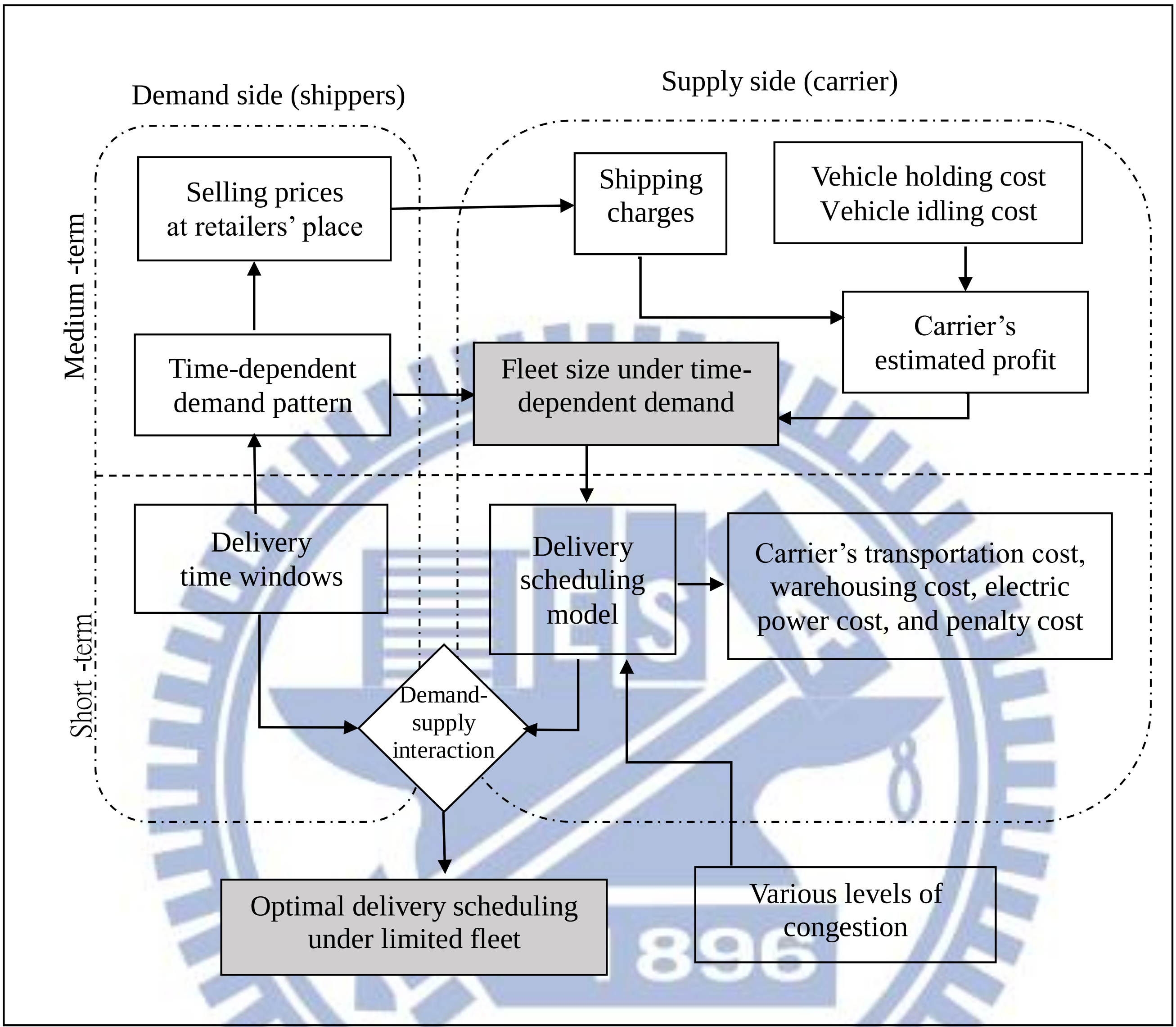
This chapter aims to analyze and optimize medium-term planning and short-term operations for multi-temperature food transportation from the view of a carrier. For medium-term planning, Chapter 3 optimizes fleet size and shipping charges for jointly distributing multi-temperature food by maximizing the carrier's profits, under time-dependent food demand. The carrier makes the decisions for medium-term planning seasonally or yearly. With the medium-term planning results, carrier can deal with the short-term operations. For short-term operations, this dissertation formulates a mathematical programming model to determine optimal departure times from the terminal for each order, for jointly distributing multi-temperature food by maximizing the carrier's profits. The scheduling for the short-term operations is restricted by the fleet size, which is decided in medium-term planning. Furthermore, this chapter explores demand-supply interaction between the carrier and shippers.

Assumption

In this dissertation, the decision maker is a carrier who delivers food ordered by shippers in the city. The carrier has terminal for temporary food storage and owns vehicles and temperature control equipment. This dissertation focuses on the delivery scheduling of a single distribution center. Therefore, the whole fleet is used by the same terminal and all orders are distributed from the same place. This chapter assumes the carrier uses the MTJD technique. As mentioned earlier, with the MTJD system, the combination of temperature ranges in the vehicle can be easily changed. This characteristic allows the MTJD technique to easily deal with the stochastic and dynamic nature of the problem. Furthermore, this chapter 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. On the other hand, shippers in this dissertation are general retailers in urban areas that sell fresh food to customers in the city. Food delivery time and shipping charges influence shippers' profits and willingness to consign. This dissertation 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.

Figure 3-1 shows the framework of Chapter 3. As shown in Figure 3-1 , the carrier seeks to maximize profit and has to make decisions for the medium-term planning, then for the short-term operations under medium-term planning results. In the medium-term planning, carrier determines optimal fleet size and multi-temperature shipping charges according to known time-dependent demand pattern. The medium-term planning results are updated seasonally. With the results of shipping charges and fleet size, the carrier schedules the daily vehicles load for jointly delivering multi-temperature food.

For the medium-term planning, this chapter assumes the carrier takes into account revenue, cost for handing vehicle, and cost for idling vehicles. The fleet size influences above-mentioned components, and the carrier seeks to maximize the profit. For the short-term operations, on the demand side, this chapter assumes the components which influence shippers' willingness to consign include delivery time and shipping charges, as mentioned earlier. On the supply side, this chapter considers the costs affected by delivery scheduling, warehousing cost, transportation cost, electric power cost, and penalty cost of the carrier. In this chapter, the vehicle travel distance is calculated by continuous approximation (Daganzo, 1999). This chapter does not solve the vehicle routing problem and only optimizes the daily scheduling for multi-temperature food delivery.



Source: This dissertation.

Figure 3- 1　The framework of Chapter 3

3.2 Model formulation

Section 3.2.1 describes the model formulation for fleet size optimization, and Section 3.2.2 illustrates the optimal departure time programming model under optimized fleet size and demand-supply interaction.

3.2.1 Fleet size

This section constructs a model to determine the optimal fleet size for carriers providing multi-temperature food delivery services. This dissertation focuses on the delivery scheduling of a single distribution center. Therefore, in this dissertation, the whole fleet is used by the same terminal and all orders are distributed from the same place.

As mentioned earlier, 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 section defines the demand time as the middle of a soft time window. The carrier may receive food orders at any time, t, during an operating day. This dissertation divides the entire study duration into many periods, and the vehicles only can be dispatched at the beginning of each period. That is, a shipper's ordering time, t, may be within a period, m, and the food would be transported at a beginning of another period which is after the ordering time, according the optimal delivery scheduling of the carrier. 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 section initially assumes that food i ordered by retailer j at time t would leave the terminal at a period that is nearest to $(u_{ijt} + s_{ijt})/2$. After determining fleet size, the departure time would be adjusted through the departure time programming model presented in Section 3.2.2.

However, in practice, widths of time windows may be three or four hours. According to Hsu et al. (2007), 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. To avoid overestimating the fleet size, for food i with the earliest and latest acceptable arrival times, U_{ijt} and S_{ijt}, respectively, this section divides it into $(U_{ijt} - S_{ijt})$ orders and allocates them to be uniformly distributed at each period between U_{ijt} and S_{ijt}. This division is only for determining fleet size. The departure time of each order will be optimized by the programming model in Section 3.2.2, 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. This fraction, $\beta_m(\Omega)$, should be between 0 and 1. 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

$$\beta_m(\Omega)=\begin{cases} 1-\Omega\chi \Big/\left[\sum_i\sum_j\sum_t \mu_{ijt}^m Q_{ijt}V_i \;/(S_{ijt}-U_{ijt})\right] & if \quad \Omega\chi<\sum_i\sum_j\sum_t \mu_{ijt}^m Q_{ijt}V_i \;/(S_{ijt}-U_{ijt}) \\ 0 & if \quad \Omega\chi\geq\sum_i\sum_j\sum_t \mu_{ijt}^m Q_{ijt}V_i \;/(S_{ijt}-U_{ijt}) \end{cases} \tag{3-1}$$

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_{ijt}^m is a binary variable. For food i ordered by retailer j at time t, if $U_{ijt}\leq m<S_{ijt}$, $\mu_{ijt}^m=1$; otherwise, $\mu_{ijt}^m=0$. This variable is for the order division mentioned earlier. Furthermore, the estimated profit function for the carrier for the entire study duration with fleet size Ω, $\pi(\Omega)$, can be formulated as the difference between estimated revenue and vehicle holding and idling costs. The profit function can be expressed as

$$\pi(\Omega)=\sum_m\left[\sum_i\sum_j\sum_t\left(\mu_{ijt}^m Q_{ijt}V_i\sum_r \varpi_{i,r}\,p_r\right)\right](1-\beta_m(\Omega))-c_1\Omega-\sum_m c_2 I_m \tag{3-2}$$

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. This dissertation describes the relationship between ordering time and possible departure time of food i ordered by retailer j at time t as the binary variable, μ_{ijt}^m. Symbol $\varpi_{i,r}$ is also a binary variable; if food i should be stored in temperature range r, $\varpi_{i,r}=1$; otherwise, $\varpi_{i,r}=0$. Let

p_r be the shipping charge for unit volume of temperature range r food. Then, 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. Furthermore, I_m can be estimated by the difference between fleet capacity and distributed volume at period m as Eq. (3-3).

$$\beta_m(\Omega) = \begin{cases} 0 & \text{if} \quad \Omega\chi < \sum_i \sum_j \sum_t \mu_{ijt}^m Q_{ijt} V_i \ /(S_{ijt} - U_{ijt}) \\ \left[\Omega\chi - \sum_i \sum_j \sum_t \mu_{ijt}^m Q_{ijt} V_i \ /(S_{ijt} - U_{ijt})\right] / \chi & \text{if} \quad \Omega\chi \geq \sum_i \sum_j \sum_t \mu_{ijt}^m Q_{ijt} V_i \ /(S_{ijt} - U_{ijt}) \end{cases} \tag{3-3}$$

The objective of the carrier in medium-term planning is to find the optimal fleet size, Ω^*, that maximizes estimated profit. Therefore, this dissertation chose the optimal fleet size, Ω^*, as the solution which yields $\max[\pi(\Omega)]$, with the constraints, $0 \leq \beta_m(\Omega) \leq 1, \quad \forall m$.

3.2.2 Delivery scheduling

This section deals with multi-temperature food shipping demand and demonstrates how the departure time of each order from the terminal and shipping charges influence 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.

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. As mentioned earlier, this dissertation 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 estimated price of selling food i, and p_r denotes the shipping charge for unit volume of temperature range r food; V_i represents the volume of unit food i. The estimated 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 $(\psi_i - F_{ij} - V_i p_r) \geq R_{ij}$. Thereby, the constraint for ensuring shipping charges for each temperature range acceptable can be constructed as

$$p_r \leq (\psi_i - F_{ij} - R_{ij}) / V_i \tag{3-4}$$

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 dissertation. 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, $\omega_{ijt}=1$ if retailer j consigns food i to the carrier at time t; otherwise, $\omega_{ijt}=0$. Thus, the level of service can be described. This dissertation measures the carrier's service level by the time-window violating rate. This rate is calculated as the ratio of the number of orders not delivered within soft time-windows to the total number of delivered orders. And the demand of the retailers' shipping orders can be constructed as

$$\omega_{ijt}=\begin{cases}1 & if \quad \left(y_{ijt}^{s}+\rho_{m}\right)\in\left[U_{ijt},S_{ijt}\right] \quad and \qquad p_{r}\le\left(\psi_{i}-F_{ij}-R_{ij}\right)/V_{i} \quad \forall i\\ 0 & if \quad \left(y_{ijt}^{s}+\rho_{m}\right)\notin\left[U_{ijt},S_{ijt}\right] \quad or \qquad p_{r}>\left(\psi_{i}-F_{ij}-R_{ij}\right)/V_{i} \quad \forall i\end{cases} \tag{3-5}$$

$$q_{ijt}=\omega_{ijt}Q_{ijt} \tag{3-6}$$

where y_{ijt}^{s} 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_{ijt}^{s}. $\left(y_{ijt}^{s}+\rho_{m}\right)$ 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. (3-5) describes the relationship between shipping charges, 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 delivery time, is not acceptable for a shipper, this shipper would not consign the shipment to that carrier.

Operation cost of MTJD system

Daganzo (1999) suggested that all costs incurred by cargoes from origin to destination should be taken into account, regardless of who pays them. Therefore, inventory cost and transportation cost are regarded as two of the major factors in this section. However, in this dissertation, the decision maker is a carrier. For a carrier, the cost from inventory activities is warehousing cost. Therefore, the major costs in this dissertation are transportation and warehousing cost. On the other hand, for shippers, the inventory cost is food value loss with time. Therefore, shippers set delivery time windows and ask carrier to pay penalty for late delivery. That is, this dissertation describes the inventory cost due to value loss by penalty cost that carrier spends for late delivery. Furthermore, we extend the cost formulation to include electric power costs for storing temperature-controlled food during vehicle routing time. Therefore, for carriers on the supply side, the costs considered for multi-temperature logistics in this section are warehousing, transportation, electric power, and penalty costs. The warehousing 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_{ijt}^{s} 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., $y_{ijt}^{s}, \forall i, j, t$) 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.

Warehousing cost

The warehousing cost includes the costs for food storage and temperature control in the terminal. Let y_{ijt}^{f} denote the time that food i ordered by retailer j at time t arrives at the terminal. Symbol B_i represents the warehousing 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 warehousing cost, C_{War}, can be formulated as:

$$C_{War} = \sum_{i}\sum_{j}\sum_{t} q_{ijt} V_i \; B_i \left(y_{ijt}^{s} - y_{ijt}^{f} \right) \tag{3-7}$$

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 is 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 dissertation calculates total vehicle travel distance by continuous approximation (Daganzo,1999). 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 $\overline{D}_m$. Symbol 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 $\bar{n}_m = \bar{L}_m / \bar{D}_m$. The total routing distance of the whole fleet can be formulated as $2E(\Delta)n_m / \bar{n}_m + kn_m / \sqrt{\sigma}$, where $E(\Delta)$ denotes the estimated 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 is for delivery truck fuel due to vehicle routing. The total variable transportation cost at period m can be calculated as $\left[2E(\Delta)n_m / \bar{n}_m + kn_m / \sqrt{\sigma}\right]O$.

The loading/unloading costs depend on the numbers of cold boxes and cabinets used for delivery. Let $N^1_{m,r}$ and $N^2_{m,r}$ denote the number of cold boxes and cold cabinets used for temperature range r food at period m, respectively. Symbols δ^1 and δ^2 represent the loading/unloading cost for a cold box and cabinet, respectively. The loading/unloading cost at period m can be expressed as $\delta^1 N^1_{m,r} + \delta^2 N^2_{m,r}$, and the total loading/unloading cost during the entire study duration can be shown as $\sum_m \sum_r \left(\delta^1 N^1_{m,r} + \delta^2 N^2_{m,r}\right)$. In sum, the transportation cost, C_{Tra}, can be formulated as

$$C_{Tra} = \sum_m \left[a_m f + \left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right]O + \sum_r \left(\delta^1 N^1_{m,r} + \delta^2 N^2_{m,r}\right) \right] \qquad (3\text{-}8)$$

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 dissertation 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^1 and γ^2 denote the capacity utilizations of cold boxes and cabinets, respectively. Symbol V^1 and V^2 denote the capacity of a cold box and cabinet, respectively, and the constraint related to cold boxes and cabinets can be constructed as

$$\gamma^1 N^1_{m,r} V^1 + \gamma^2 N^2_{m,r} V^2 \geq \sum_i \sum_j \sum_t \theta^m_{ijt} q_{ijt} V_i \quad \forall m, r \tag{3-9}$$

where θ^m_{ijt} is a binary variable. If the departure time from the terminal for food i ordered by retailer j at time t is m, $\theta^m_{ijt} = 1$; otherwise, $\theta^m_{ijt} = 0$. Let V'^1 and V'^2 denote the volume of a cold box and cabinet, respectively. Symbol γ^3 denotes the capacity utilization of a vehicle. Since fleet size is limited as the results of medium-term planning, the total volume of cold boxes and cabinets at each period should be equal to or smaller than the fleet capacity. Therefore, the constraint related to fleet capacity and cold box/cabinet usage can be expressed as

$$\sum_r \left(N^1_{m,r} V'^1 + N^2_{m,r} V'^2 \right) \leq \gamma^3 \chi \Omega^* \quad \forall m \tag{3-10}$$

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. This dissertation estimates the usage time by routing distance and average vehicle speed. Therefore, the electric power cost , C_{Ene}, can be calculated as

$$C_{Ene} = \sum_m \left(\phi^1_r N^1_{m,r} + \phi^2_r N^2_{m,r} \right) \left[2E(\Delta) \overline{n}_m / n_m + k n_m / \sqrt{\sigma} \right] O / v_m \tag{3-11}$$

where ϕ_r^1 and ϕ_r^2 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.

Penalty cost

Regarding the penalty cost, according to Hsu et al. (2007), 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 $\left(y_{ijt}^s + \rho_m - s_{ijt}\right)$, 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

$$C_{Pen} = \sum_m \sum_i \sum_j \theta_{ijt}^m b_{ijt} q_{ijt} P_i d_{ij} \left[\lambda\left(y_{ijt}^s + \rho_m - s_{ijt}\right)\right]^{\zeta_i} \tag{3-12}$$

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 dissertation calculates vehicle travel time at period m, ρ_m, using continuous approximation (Daganzo, 1999), as discussed earlier. Furthermore, the number of vehicles used at period m can be estimated as $\left(n_m \overline{D}_m\right)/\overline{L}_m$ 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 discussed earlier in the section of transportation cost calculation. Finally, The ρ_m can be expressed as

$$\rho_m = \frac{2E(\Delta)n_m / \overline{n}_m + kn_m / \sqrt{\sigma}}{v_m\left(n\overline{D}_m / \overline{L}_m\right)} \tag{3-13}$$

Furthermore, ρ_m can be simplified as

$$\rho_m = \left\lfloor 2E(\Delta) + k\overline{n}_m / \sqrt{\sigma} \right\rfloor / v_m \tag{3-14}$$

Then the carrier's profit can be formulated as

$$\sum_i \sum_j \sum_t q_{ijt} V_i \; p_r - \left(C_{War} + C_{Tra} + C_{Ene} + C_{Pen}\right).$$

3.2.3 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. 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., $y_{ijt}^s, \forall i, j, t$) and shipping charge for each temperature range (i.e., $p_r, \forall r$).

$$Max \quad \left\{ \left(\sum_i \sum_j \sum_t p_r V_i \; Q_{ijt} \right) - \left(C_{War} + C_{Tra} + C_{Ele} + C_{Pen} \right) \right\} \tag{3-15a}$$

s.t.

$$p_r \le \left(\psi_i - F_{ij} - R_{ij} \right) / V_i \quad \forall r \tag{3-15b}$$

$$C_{War} = \sum_i \sum_j \sum_t q_{ijt} V_i \; B_i \left(y_{ijt}^s - y_{ijt}^f \right) \tag{3-15c}$$

$$C_{Tra} = \sum_m \left[a_m f + \left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma} \right] O + \sum_r \left(\delta^1 N_{m,r}^1 + \delta^2 N_{m,r}^2 \right) \right] \tag{3-15d}$$

$$C_{Ene} = \sum_m \left(\phi_r^1 N_{m,r}^1 + \phi_r^2 N_{m,r}^2 \right) \left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma} \right] O / v_m \tag{3-15e}$$

$$C_{Pen} = \sum_m \sum_i \sum_j \theta_{ijt}^m b_{ijt} q_{ijt} P_i d_i \left[\lambda \left(y_{ijt}^s + \rho_m - s_{ijt} \right) \right]^{\zeta_i} \tag{3-15f}$$

$$\rho_m = \left[2E(\Delta) + k\bar{n}_m / \sqrt{\sigma} \right] / v_m \tag{3-15g}$$

$$\gamma^1 N_{m,r}^1 V^1 + \gamma^2 N_{m,r}^2 V^2 \ge \sum_i \sum_j \sum_t \theta_{ijt}^m q_{ijt} V_i \quad \forall m, r \tag{3-15h}$$

$$\sum_r \left(N_{m,r}^1 V'^1 + N_{m,r}^2 V'^2 \right) \le \gamma^3 \chi \Omega^* \quad \forall m \tag{3-15i}$$

Eq.(3-15a) represents the objective function that maximizes profit through the study duration. Eq.(3-15b) expresses the upper bound of the shipping charge for each temperature range. Eq.(3-15c), (3-15d), (3-15e) and (3-15f) define the warehousing, transportation, energy and penalty costs as Eq.(3-7), (3-8), (3-11), and (3-12), respectively. Moreover, Eq.(3-15g) represents the travel time estimation function as Eq.(3-14). Eq.(3-15h) 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.(3-15i) requires the total volume of cold boxes and cabinets at each period be equal to or smaller than the fleet capacity.

As the model shows, there are lots of variables in the programming and many of them depend on each other. For example, the numbers of cold boxes and cabinets at each period depend on departure time combinations. The penalty cost of each shipment also depends on departure time. For each shipment, there exists penalty calculation. Therefore, it is difficult and time-consuming to find an optimal solution for the proposed model, and heuristic algorithm is required. This dissertation describes the heuristic selection and parameters setting for algorithm in Section 3.3.

Demand-supply interaction

Based on the fleet size optimization model in Section 3.2.1, the departure time from the terminal for each order of food for each temperature range can be determined by model in Section 3.2.2. The demand-supply interaction between departure time and shipments are analyzed by the model described above. On the demand side, this dissertation estimates shipping volume by aggregating shippers' carrier choices. The shipping volume of food i ordered by retailer j at time t is estimated by Eq.(3-5)-(3-6) and used as input parameters for the departure time determining programming model on the supply side (Eq.(3-15a)-(3-15i)). The departure time and shipping charges determined by Eq.(3-15a)-(3-15i) affect shippers' choices. This dissertation 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 (Eq.(3-15a)-(3-15i)). Then shipping demand of food i ordered by retailer j at time t is estimated by Eq.(3-5)-(3-6). 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. According to Eq.(3-5)-(3-6), the interaction is based not only on service level (delivery time) but also shipping charge. During the interaction process, variation due to service level is much more sensitive than shipping charge because the carrier chose the lowest acceptable shipping charge among all shippers as the optimal scheme. The optimal charge varies only when the shipper with the lowest acceptable charge withdraw the shipment. However, the shipping charges for each temperature are medium-term planning results in practice. Therefore, the shipping charges are determined at the first time of the programming and fixed during short-term operations.

The most famous theory regarding demand-supply is Flow Conservation. Compared with Flow Conservation Theory, the demand nodes and in-bound flow can be described as the shippers and their demand in proposed model, respectively. However, the characteristics of demand contains not only volume but delivery time windows and temperature ranges. As for the out-bound flow, it can be analogy with the distributed volume to each shippers, that is, delivery service, at different dispatching time for different temperature ranges. If the in-bound flow (the demand volume) is not equal to the out-bound (distributed volume), there would exist penalty cost for the order of food. This dissertation deals with the time-dependence of the problem by dividing the study duration into many small periods. On the other hand, the food is divided into several different ranges according to the suitable storage temperature. That is, this dissertation analyzes the problem using multi-periods and multi-temperature approach. Without multi-periods analysis, huge penalty cost due to violating time-windows might be resulted in. Without multi-temperature analysis, although the variables related to temperature can be removed, then the difficulty of solving the problem decreases, the equipment usage for different temperature ranges cannot be calculated accurately. Under such condition, if the equipment with correct temperature is not sufficient, the food quality would be influenced seriously.

3.3 Algorithm

This dissertation made trial runs to examine the difficulty of solving the food distribution problem. The solution includes the time each order of multi-temperature food leaves terminal, and there are various combinations of departure times for all orders. For a problem with a carrier who delivers ℓ orders of food to different retailers in an operating day, which is divided into m_1 periods, there are m_1^{ℓ} feasible solutions. Therefore, the time for solving the proposed model increases exponentially with the number of decision variables. We assume departure time for each order is natural numbers, in terms of the unit of time being studied. Therefore, a general integer programming model is formulated since all decision variables are positive integers. Furthermore, since the departure time must be integer, for ℓ orders, there are ℓ explicit constraints, and the number of feasible solutions decreases. On the other hand, many variables in the cost functions depend on the decision variables. For example, the numbers of cold boxes and cabinets at each period depend on delivery cycle combinations. Therefore, for a problem with m periods and ℓ ranges, there are $m\ell$

element constraints for cold boxes and cabinets, respectively. In addition, the penalty cost of each shipment also depends on departure time. For each shipment, there is an element constraint for penalty calculation. According to Hillier and Lieberman (2009), the process of applying constraint programming to integer programming problems involves efficiently finding feasible solutions that satisfy all constraints and searching for the optimal solution among these solutions. The methods include enumerating solutions and adding a constraint that tightly bounds the objective function to values that are very near to what is anticipated for the optimal solution. In sum, due to the large numbers of constraints and feasible solutions, it is difficult and time-consuming to find an optimal solution; thus approximate methods are required. The most commonly used approaches are the genetic algorithm (GA) and simulated annealing (SA). However, adopting GA tends to be computationally expensive (Mishra et al., 2003), and the crossover is not suitable for the proposed model because it is not a sequence problem. As for SA, proposed by Kirkpatrick et al. (1983), it has been extensively used in solving many difficult optimization problems (Paik and Soni, 2007). The SA algorithm is based on Metropolis et al. (1953), which was originally proposed as a means of finding the equilibrium configuration of a collection of atoms at a given temperature. The major advantage of the SA algorithm is the ability to avoid becoming trapped in the local optimal. Therefore, this dissertation adopts the SA algorithm to solve the optimal departure time for each order of food. This section 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 hour(s). In practice, delivery time windows usually exceed three hours. Therefore, this dissertation 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}).

In practice, carriers usually provide the service of delivering food on the same day of ordering. To solve the problem effectively, this dissertation sets the time for solving the proposed model to be 0.5 hour. After several trials, this dissertation sets the SA algorithm parameters as follows.

The values of the SA algorithm parameters include (1) the initial temperature, $T_0 = 50$; (2) the decreasing ratio of temperature is 0.8; (3) the number of temperature decreases is 20; and (4) the number of moves at each temperature is 1000. Conditions (1)-(3) are stop criteria for the SA. Condition (4) is the stop criterion for the Metropolis algorithm (Metropolis et al., 1953). Referring to Heragu and Alfa (1992) and Yan and Luo (1999), the SA algorithm can be described as follows.

Step 0. Employ initial solution, H, and calculate its objective function, $Z(H)$.

Step 1. At temperature T_x, implement the Metropolis algorithm:

1.1 Randomly choose an order of food i ordered by retailer j at time t and randomly generate a variable $\tau_1 \sim U(0,1)$; if $\tau_1 \geq 0.5$, $y^s_{ijt} = y^s_{ijt} + 1$; otherwise, $y^s_{ijt} = y^s_{ijt} - 1$.

1.2 To deliver multi-temperature food jointly and reduce unloading time, for any food ordered by the same shipper with the same time windows, the algorithm checks whether their departure times are the same. Therefore, for food i and i' ordered by retailer j and j' at time t and t', respectively, if $j = j'$, $S_{ijt} = S_{i'j't'}$ and $U_{ijt} = U_{i'j't'}$, then $y^s_{ijt} = y^s_{i'j't'}$. Let the altered solution be the adjacent solution, H'. Calculate the objective value $Z(H')$ for the adjacent solution H'.

1.3 Determine whether the new solution is accepted.

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

1.3.2 If $\Delta < 0$, then $H = H'$; else randomly generate a variable $\tau_2 \sim U(0,1)$. If $\exp(-\frac{\Delta}{T_x}) \geq \tau_2$, then $H = H'$; else go to Step1.

1.3.3 If the stop criteria of the Metropolis algorithm (Condition (4)) is satisfied, then go to Step 2, else go to Step 1.

Step 2. If the stop criteria of the SA algorithm (Conditions (1)-(3)) are satisfied, then go to Step 3; else let $x = x + 1$ and $T_{x+1} = 0.8T_x$, and go to Step 1.

Step 3. Output the optimal departure time from terminal for each order of multi-temperature range foods, $H*$.

3.4 Case Study

This section presents a numerical example to demonstrate the application of the model constructed in Sections 3.2. This example covers an area of 500 square kilometers 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: Range 1 (below -30$^\circ C$), Range 2 (-30$^\circ C$ ~ -18$^\circ C$), Range 3 (-2$^\circ C$ ~+2$^\circ C$), Range 4 (0$^\circ C$ ~ 7$^\circ C$), and Range 5 (18$^\circ C$, constant) as shown in Table 3-1.

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 minutes, which is the problem solving time discussed in Section 3.3. This dissertation assumes one operating day, namely 24 hours, as the entire study duration, with the unit of time for the study being 1 hour. 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.

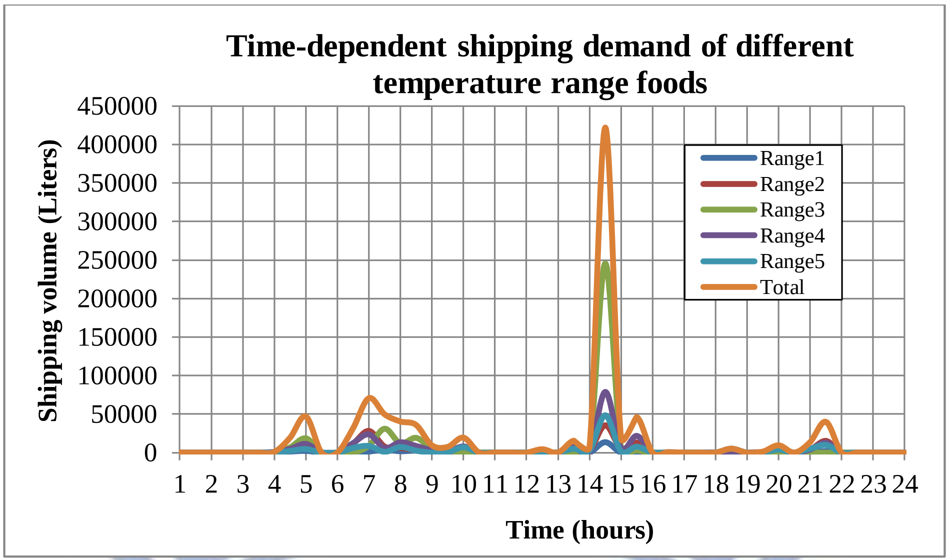
Time-dependent demand

The temporal pattern of demand during the entire study is shown in Figure 3-2. In Figure 3-2, the demand time is approximately estimated as the middle of the time window. 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 3-2. The temporal pattern of road speeds is estimated by data from the Taipei City Department of Transportation, as shown in Figure 3-3, which reveals rush hours.

Table 3- 1 Initial values of food

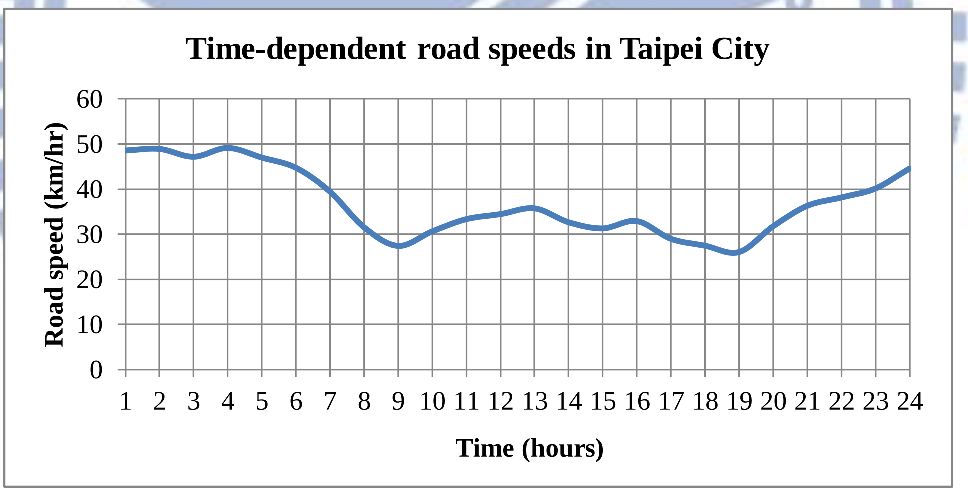
Temperature range	Food code	Food	V_i (L)	P_i (NT$)	B_i (NT$)	ζ_i
Range 1 (<-30 $^\circ C$)	1	Sashimi	22	950	0.008	2.20
Range 2 (-30 $^\circ C$ ~-18 $^\circ C$)	2	Ice cream	10.5	65	0.007	1.05
	3	Frozen steamed buns with stuffing	12	350	0.007	1.20
	4	Frozen steamed dumplings	12	250	0.007	1.20
	5	Frozen vegetables	15	200	0.007	1.50
	6	Frozen meat	15	400	0.007	1.50
Range 3 (-2 $^\circ C$ ~+2 $^\circ C$)	7	Fish	20	700	0.006	2.00
	8	Duck	17	400	0.006	1.70
	9	Chicken	18	500	0.006	1.80
	10	Mutton	18	600	0.006	1.80
	11	Pork	18	500	0.006	1.80
	12	Beef	20	800	0.006	2.00
Range 4 (0 $^\circ C$ ~+7 $^\circ C$)	13	Ham	13	50	0.005	1.30
	14	Bean curd	15	60	0.005	1.50
	15	Milk	14	800	0.005	1.40
	16	Juice	14	500	0.005	1.40
	17	Vegetables	16	500	0.005	1.60
Range 5 (+18 $^\circ C$ ~)	18	Chocolate	10.5	150	0.004	1.05
	19	Cookie	12	45	0.004	1.20
	20	Soft drink	12	60	0.004	1.20

Source: This dissertation.



Source: This dissertation.

Figure 3- 2 Time-dependent shipping demand for different temperature range foods



Source: This dissertation.

Figure 3- 3 Time-dependent road speeds in Taipei City

Table 3- 2 Value of parameters related to carriers

Definition	Value
Vehicle capacity (m^3)	16
Fixed cost for dispatching a vehicle (NT$)	200
Loading/unloading cost per box (NT$)	15
Loading/unloading cost per cabinet (NT$)	45
Cold box capacity / volume (Liters)	90 / 194
Cold cabinet capacity / volume (Liters)	936 / 2118
Electric power cost per cold box per hour (NT$) (temperature range 1, 2, 3, 4, 5)	1.14, 1.026, 0.988, 0.775, 0.540
Electric power cost per cold cabinet per hour (NT$) (temperature range 1, 2, 3, 4, 5)	3.42, 3.078, 2.964, 2.326, 1.619

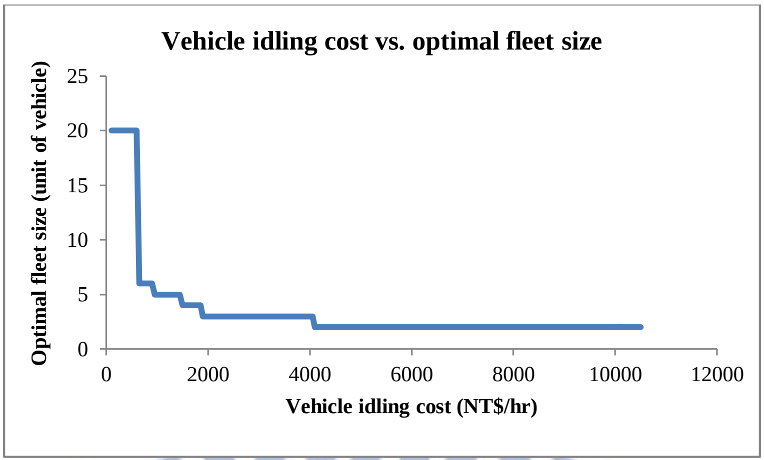
Source: This dissertation.

Optimal fleet size

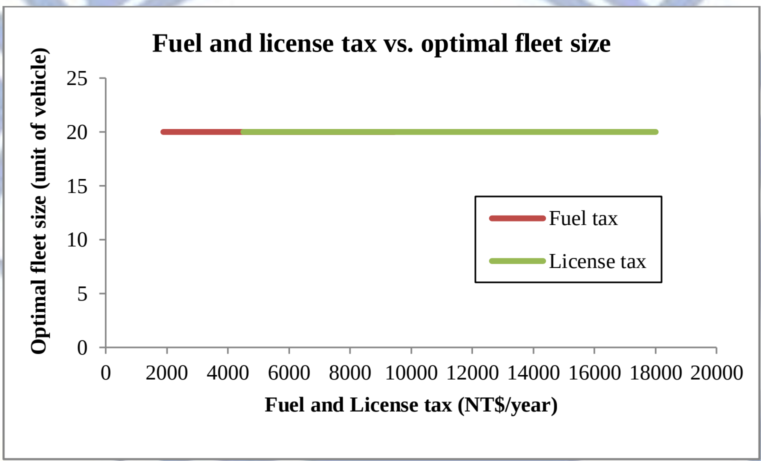
This dissertation estimates vehicle holding cost by fuel tax, license tax, and vehicle purchase cost divided by its lifetime. The fuel tax is levied by the government and is based on the air displacement of vehicle. The optimal fleet size for the carrier is 20 vehicles when the vehicle purchase cost and idling cost per period are NT$1,550,000 and NT$500, respectively, with the demand pattern shown in Figure 3-2. Moreover, the vehicle handling and idling costs vary with socioeconomic conditions, business cycles, and government policy. This dissertation 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. Figure 3-4 illustrates vehicle idling cost per period and vehicle handling cost vs. optimal fleet size, respectively. As Figure 3-4 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 Figure 3-4, 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 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.

Shipping charges

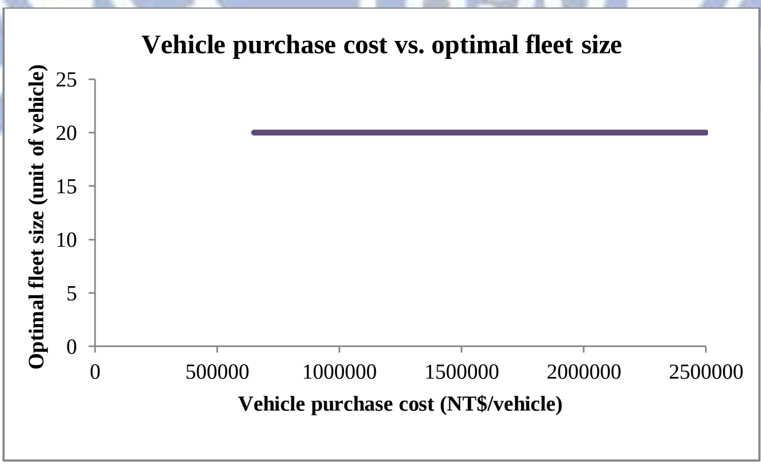
To calculate the upper bound of the acceptable shipping charge for each temperature range, the dissertation collects all data related to estimated profit and other costs for all of shippers. To maximize profits, the carrier should choose the highest upper bound of all acceptable shipping charges to be 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 dissertation assumes the charges for next day delivery are 0.8 times those for same day delivery. The results after rounding are shown in Table 3-3. Because this dissertation does not consider competition between carriers, the results in Table 3-3 may be a little higher than service charges in practice. However, the results are still reasonable as compared with practice.



(a) Vehicle idling cost vs. optimal fleet size



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



(c) Vehicle purchase cost vs. optimal fleet size

Source: This dissertation.

Figure 3- 4 Vehicle idling/holding cost vs. optimal fleet size

Table 3- 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~-18°C)	1.2	1.0
Range 3 (-2°C~+2°C)	1.0	0.8
Range 4 (0°C~7°C)	0.7	0.5
Range 5 (18°C~)	0.5	0.4

Source: This dissertation.

Delivery scheduling

Table 3-4 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 transport 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 delivering 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 3-4. 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.

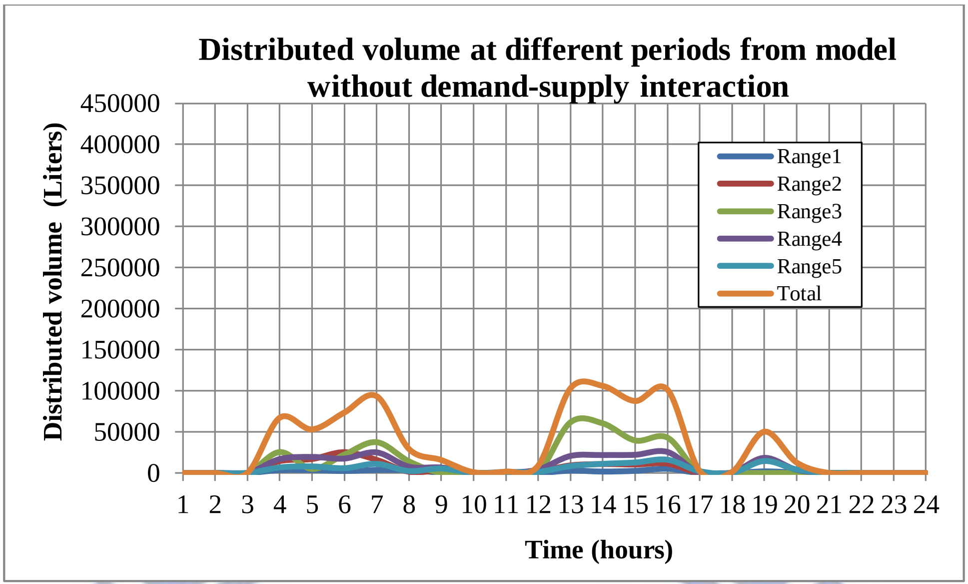
Figures 3-5 (a) and (b) show the distributed volume for different temperature range foods at different periods under optimal departure time programming without and with demand-supply interaction, respectively. Figure 3-5 (a) shows the results where a carrier abandons shipments that cannot be delivered within an acceptable time in the case without supply-demand interaction. Figure 3-5 (b) shows the results when solving with demand-supply interaction. Comparing Figure 3-5 with Figure 3-2, 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 Figure 3-2, are dispersed and distributed during 11:00-16:00, which is shown in Figure 3-5 (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 is needed.

In Figure 3-5 (b), the results obtained with demand-supply interaction show that some food distributed before 12:00 or after 15:00, as shown in Figure 3-5 (a), are withdrawn or moved to other periods. Thereby, the penalty and other delivery costs for these 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.

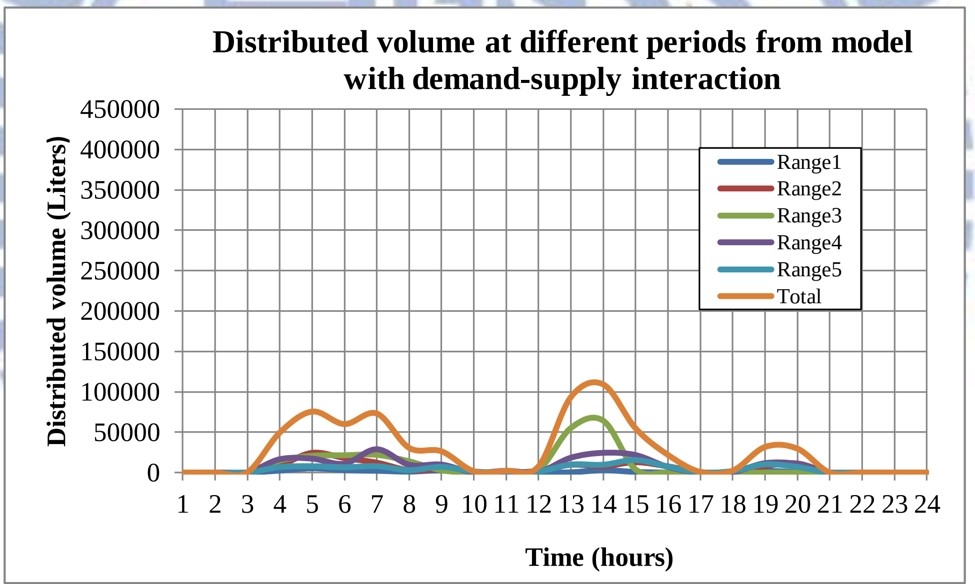
Table 3- 4 Delivered temperature ranges at different periods from results obtained without and with demand supply interaction

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	/	/

Source: This dissertation.



(a) without demand-supply interaction



(b) with demand-supply interaction

Source: This dissertation.

Figure 3- 5 Optimal distributed volume of various temperature range foods at different periods

Table 3-5 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 dissertation reprograms the optimal departure time for accepted orders and abandons some orders after rounds of interaction. However, this dissertation 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 3-5, Range 3 food reduced most markedly after rounds of interactions; this is because 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 Ranges 1 and 5 are reduced more than 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 warehousing 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 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 dissertation 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, as mentioned in Section 3.2.1. The time window 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 3-5. 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.

Table 3- 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 (Liters)	Initial volume	Revised volume	
Range 1	34,320	32,450	23,320
Range 2	156,546	141,611	130,556
Range 3	361,142	310,658	222,296
Range 4	233,600	212,255	190,675
Range 5	131,193	112,184	103,349
Total distributed volume	916,801	809,157	670,195
Warehousing cost (NT$)		68,127 (14.76%)	55,748 (16.40%)
Penalty cost (NT$)		92,973 (20.15%) Time window violating rate: 6.02%	67,023 (19.71%) 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%)
Fuel 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.

Source: This dissertation.

Costs and profits

Table 3-5 also compares different costs and profits, using percentage of total cost, for the results obtained without and with demand-supply interaction, respectively. As shown in Table 3-5, 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 3-5, 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 fuel 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 decreases, 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 costs but greenhouse gas emissions while maintaining service levels. Furthermore, it can reduce emission costs if the carrier is levied a carbon tax. Regarding warehousing 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 3-5. 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.

Other detail results

Table 3-6 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 Figure 3-5. 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.

The numbers of vehicles, cold boxes, and cold cabinets needed for all periods without and with demand-supply interaction are shown in Table 3-7. The fourth, fifth, eighth, and ninth columns of Table 3-7 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 3-7, the carrier used eight, six, three, two, and three cold boxes for Ranges 1, 2, 3, 4, and 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 3-7, 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 Figure 3-3 with Table 3-7, 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.

Table 3- 6　Distributed orders from results obtained without and 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)]

Note: Parentheses denote food code and amount.

Source: This dissertation.

Table 3-6 *(Continued)*

Period	Temperature ranges	Stop codes and distributed food
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 [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.
Source: This dissertation.

Table 3- 7 Equipment usage and vehicle travel time from results obtained without and with demand-supply interaction

Period	Result without demand-supply interaction: Number of vehicles (units)	Average vehicle travel time (hours)	Number of cold boxes (units)	Number of cold cabinets (units)	Result with demand-supply interaction: Number of vehicles (units)	Average vehicle travel time (hours)	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

3.5 Summary

This chapter 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.

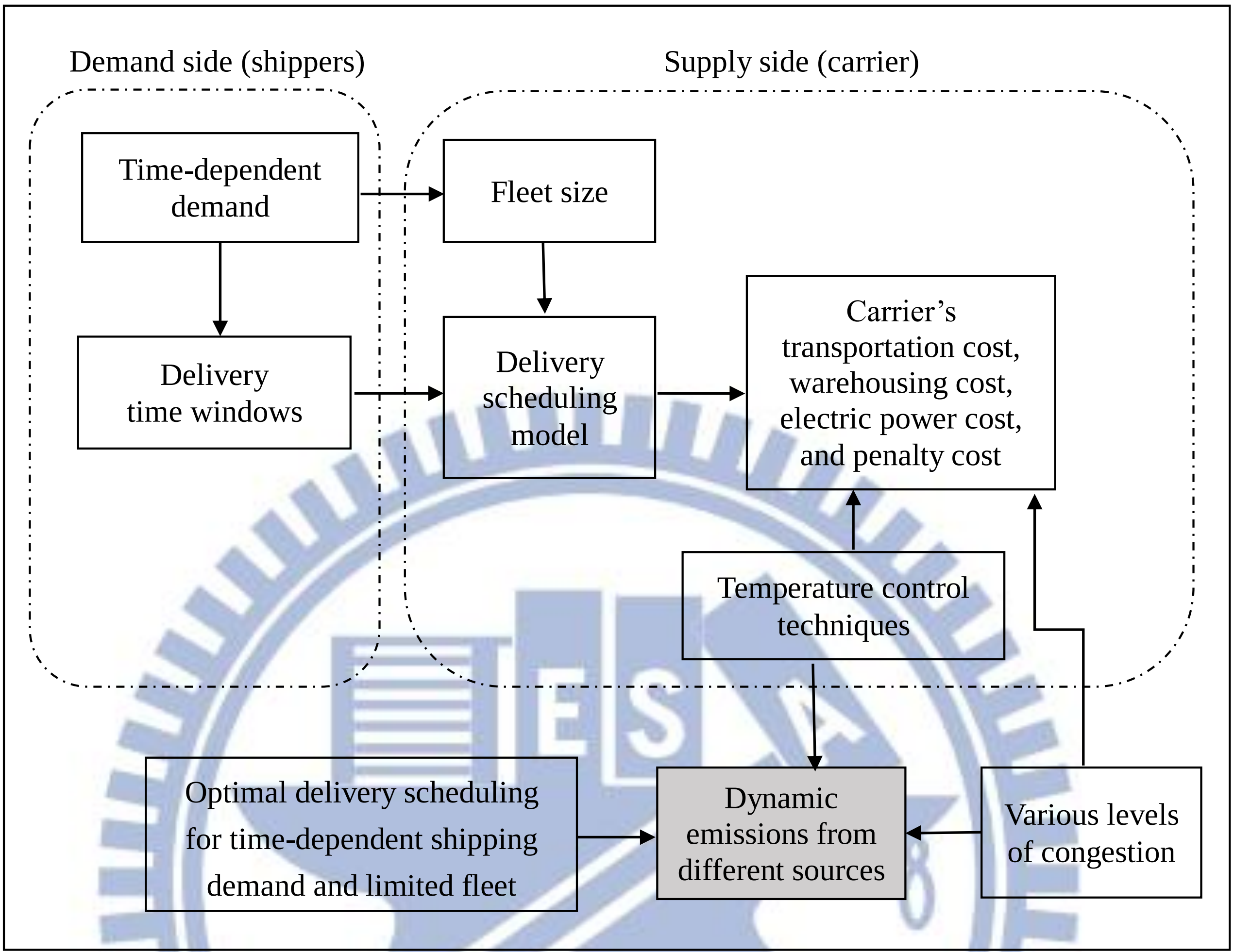
A numerical example illustrates the application of the proposed model. The results suggest that carriers determine departure times of multi-temperature food with demand-supply interaction to increase profit. In addition, when shipping demand exceeds fleet capacity, the carrier should deliver food of medium temperature ranges with priority because delivering such food yields more profit.

Chapter 4 Greenhouse emissions for multi-temperature food delivery system

This chapter follows the optimal delivery scheduling model for temperature-controlled food formulated in Section 3.2.2, dividing the entire study duration into many periods. Using the model in Section 3.2.2, the delivery list, number of vehicles, and equipment dispatched for each period under minimized delivery costs are determined. Furthermore, this chapter formulates model to estimate and analyze the emissions of the two systems under the minimized delivery costs.

4.1 Introduction to the problem

This chapter formulates mathematical models to estimate and compare the emissions of the MTJD and TMVD system under time-dependent demand and various levels of traffic congestion. Figure 4-1 shows the framework of this chapter. This chapter follows the delivery scheduling model constructed in Section 3.2.2. As mentioned earlier, Section 3.2.2 constructs a model to determine optimal departure times from the terminal for each order by maximizing the carrier's profits. The scheduling is restricted by carrier's fleet size. After the delivery scheduling is determined, the emissions from each sources can be estimated. For this reason, Chapter 4 aims to analyze the relationships among distributed food volume and characteristics, traffic conditions, and dynamic emissions from different sources in the delivery systems, taking into account different temperature control techniques. The techniques this chapter discusses include the MTJD and TMVD system, which are introduced in Chapter 1. Moreover, this chapter analyzes and compares the carbon footprints of multi-temperature foods in the two delivery systems.



Source: This dissertation.

Figure 4- 1 The framework of Chapter 4

Assumption

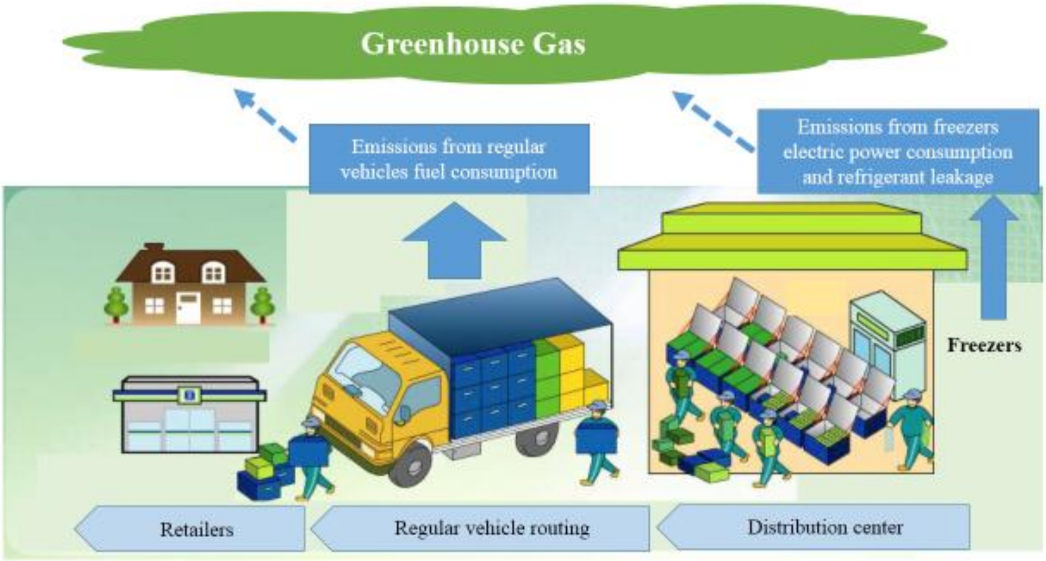
This chapter focuses on emissions due to transporting temperature-controlled food from terminal to retailers, the emissions from energy (fuel and electric power) consumption and refrigerant leakage during this process. In the MTJD system, vehicle routing consumes fuel, and freezers installed at the terminal not only consume electric power but result in refrigerant leakage. All the above-mentioned activities generate greenhouse gas. For the TMVD system, as discussed in Chapter 1, the vehicles for different temperature ranges consume fuel and result in refrigerant leakage during not only routing but loading/unloading time. These activities in the TMVD system generate greenhouse gas. Emissions due to food storage at warehouses are not taken into account since, for the two systems, the refrigeration equipment for storing food at the warehouses are the same and operate all the time. This dissertation assumes food is stored at the terminal until distribution. The energy consumption and refrigerant leakage at the terminal warehouse are not affected by the results of delivery scheduling and have no influence on the comparisons between the two systems. Furthermore, the scope of emission calculations for road freight must be defined with respect to activity (McKinnon and Piecyk, 2009). That is, the emissions due to fuel consumption are estimated by the travel distance, speed, and payload of the vehicles. The emissions estimation for electric power consumption depends on the cold boxes usage time. Finally, the refrigerant leakage, as discussed earlier, this chapter focuses on the sources of emissions which depend on delivery scheduling, that is, the refrigerant used in the delivery process. The sources of emissions in other places, such as manufacture factories and retailer stores, are not taken into account in this chapter.

4.2 Model Formulation

This chapter formulates emission estimation models for the MTJD and TMVD systems. The scope of emission calculations for road freight must be defined with respect to activity (McKinnon and Piecyk, 2009). As discussed earlier, this chapter focuses on emissions due to transporting temperature-controlled food from terminal to retailers; that is, the emissions from energy (fuel and electric power) consumption and refrigerant leakage during this process. The emissions estimation model for the MTJD and TMVD systems are formulated in Section 4.2.1 and 4.2.2, respectively.

4.2.1 MTJD system

Figure 4.2 shows the sources of emissions in the MTJD system. As shown in the figure, the sources of emissions include fuel consumption of regular vehicles and electric power consumption and refrigerant leakage of freezers at terminal. The freezers is used for gathering cold into accumulators; thus, the accumulators can be used for temperature control during delivery process. The estimation method for each source of emissions in the MTJD system is described as follows.



Source: This dissertation.

Figure 4- 2 The sources of emissions in the MTJD system

Emissions from fuel consumption in the MTJD system

According to IPCC (2006), emissions from road transportation are calculated by multiplying fuel consumption with a CO_2 emission factor. Fuel consumption can be estimated by vehicle kilometers travelled (VRT). Emissions from the fuel consumption of regular vehicles in the MTJD system depend on vehicle routing but not on loading/unloading time because food is stored in cold boxes with replaceable cold accumulators to maintain temperature. This chapter follows Section 3.2.2 to calculate total vehicle travel distance by continuous approximation (Daganzo, 1999). For the MTJD system, symbol n_m denotes the number of shippers the carrier serves at period m, and the average distributed volume for each shipper at period m is $\overline{D}_m$. Symbol σ represents the number of shippers per unit area; $\overline{L}_m$ denotes the average vehicle load at period m. Thereby, the average number of shippers served by the same vehicle at period m, $\overline{n}_m$, can be calculated as $\overline{n}_m = \overline{L}_m / \overline{D}_m$. Thus, the total routing distance of the whole fleet at period m can be formulated as $2E(\Delta)n_m / \overline{n}_m + kn_m / \sqrt{\sigma}$, where $E(\Delta)$ denotes the estimated distance from terminal to the shippers' retail stores. However, except for routing distance, fuel consumption also depends on vehicle payload and speed. Section 3.2.2 does not take into account the influence of food weight. For further analysis, this chapter refers to Suzuki (2011) to analyze the effect of vehicle payload on fuel consumption. For the MTJD system, symbol Γ_m represents average vehicle payload at period m that measures the deviation of a vehicle's fuel consumption rate from the average value based on the payload. Let Φ denote the average payload in the long run of the MTJD system. Thus, Γ_m is expressed as

$$\Gamma_m = \left(\sum_i \sum_j \sum_t \kappa'^{m}_{ijt}\, q_{ijt} W_i + \overline{W}_r\, N_{m,r} \right) / \Phi \tag{4-1}$$

where W_i is the weight of unit food i, and $\overline{W}_i$ denotes the weight of a cold box in the MTJD system, which includes the weight of the box and cold accumulators. Symbol $N^1_{m,r}$ represents the number of cold boxes used for temperature range r food at period m. Symbol κ_{ijt}^{m} is a binary variable; if food i ordered by retailer j at time t is dispatched at period m, $\kappa_{ijt}^{m}=1$; otherwise, $\kappa_{ijt}^{m}=0$. Let o_m represent the fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m, which is the road speed at period m. Thus, the fuel consumption of the MTJD system at period m can be calculated as $\left(2E(\Delta)\overline{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m$. Let the emission factor of unit fuel be α_{oil}. Then, the emissions from fuel consumption of the MTJD system, G_{oil}, are given by

$$G_{oil} = \sum_{m}\left(2E(\Delta)\overline{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m \alpha_{oil} \tag{4-2}$$

Emissions from electric power consumption in the MTJD system

As for electric power consumption of freezers at the terminal, as discussed in Chapter 1, the freezers gather cold into cold accumulators. Therefore, electric power consumption depends on the number of cold accumulators used and usage time of the cold accumulators. Since cold accumulators are used for temperature control during transport, usage time can be calculated as the sum of vehicle routing and loading/unloading times. Let the both loading and unloading time for one cold box be h. Thus, the usage time of temperature range r cold accumulators at period m can be expressed as $\left\lfloor \left(2E(\Delta)\overline{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m \right\rfloor + 2hN_{m,r}^{1}$, which is the sum of routing and loading/unloading time. Let X_r be the number of cold accumulators used for one temperature range r cold box. Furthermore, the number of cold accumulators used for temperature range r food at period m can be calculated as $N^1_{m,r} X_r$. The emissions from electric power consumption of the MTJD system, $G_{electricity}$, can be expressed as

$$G_{electricity} = \sum_m \sum_r \left(N^1_{m,r} X_r\right)\left(\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m + 2hN^1_{m,r}\right) e \alpha_{electricity} \tag{4-3}$$

where e is the electric power consumption per unit time, unit cold accumulator. Symbol $\alpha_{electricity}$ is the emission factor of unit electric power consumption.

Emissions from refrigerant leakage in the MTJD system

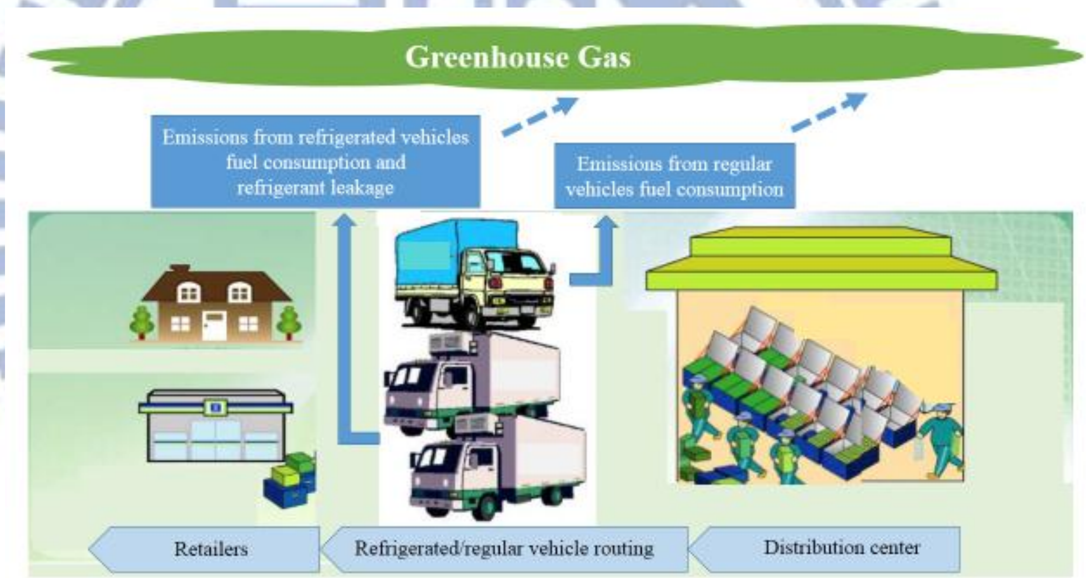
Regarding emissions from refrigerant leakage, for the MTJD system, the refrigerant is inside freezers installed at terminals, and leakage depends on the operating time of the freezers. That is, leakage depends on the time for accumulating cold, which depends on the usage time of the cold accumulators (i.e., the sum of vehicle routing and loading/unloading time). Therefore, emissions from the refrigerant leakage of the MTJD system, $G_{refrigerant}$, can be calculated as

$$G_{refrigerant} = \sum_m \sum_r \left(N^1_{m,r} X_r\right)\left(\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m + 2hN^1_{m,r}\right) K_r \tag{4-4}$$

where K_r is the emissions from refrigerant leakage due to accumulating cold for a temperature range r accumulator per unit time. The method for estimating K_r is presented in Section 4.2.3.

4.2.2 TMVD system

For the TMVD system, as discussed earlier, the vehicles for different temperature ranges consume fuel and result in refrigerant leakage during routing and loading/unloading time. The above-mentioned activities generates greenhouse gas. Figure 4-3 shows the sources of emissions in the TMVD system. As shown in the figure, the sources of emissions in the TMVD system include fuel consumption and refrigerant leakage of different temperature ranges vehicles, during the time duration of routing on the routes and loading/unloading food at shippers' place. The estimation method for each source of emissions is described as follows.



Source: This dissertation.

Figure 4- 3 The sources of emissions in the TMVD system

Emissions from fuel consumption in the TMVD system

Following Section 3.2.2, this chapter calculates total vehicle travel distance by continuous approximation (Daganzo, 1999). Let $n'_{m,r}$ denote the number of shippers the carrier serves at period m with temperature range r vehicles. The average temperature range r distributed volume for each shipper at period m is $\bar{D}'_{m,r}$, in the TMVD system. Symbol σ represents the number of shippers per unit area; $\bar{L}'_{m,r}$ denotes the average load of temperature range r vehicles at period m. Thereby the average number of shippers served by the same temperature range r vehicle at period m, $\bar{n}'_{m,r}$, can be calculated as $\bar{n}'_{m,r} = \bar{L}'_{m,r} / \bar{D}'_{m,r}$. Furthermore, the total routing distance of the whole temperature range r fleet at period m can be formulated as $\left(2E(\Delta)\bar{n}'_{m,r} / n'_{m,r} + kn'_{m,r} / \sqrt{\sigma}\right)$, where $E(\Delta)$ denotes the expected distance from terminal to the shippers' retail stores. Symbol k is a constant; $k \approx 0.57$ when distance is calculated using the Euclidean Metric, and $k \approx 0.82$ if the distance is computed as Metric. As mentioned earlier, this dissertation refers to Suzuki (2011) to analyze the effect of vehicle payload on fuel consumption. Let $\Gamma'_{m,r}$ represent the average vehicle payload at period m that measures the deviation of a temperature range r vehicle's fuel consumption rate from the average value based on the payload in the TMVD system. Symbol Φ'_r denotes the average payload for temperature range r vehicles in the long run of the TMVD system. Thus, $\Gamma'_{m,r}$ is expressed as

$$\Gamma'_{m,r} = \left(\sum_i \sum_j \sum_t \kappa'^{m}_{ijt} \, q_{ijt} W_i + \bar{W}' N'_{m,r} \right) / \Phi'_r \tag{4-5}$$

where W_i is the weight of unit food i, and $\bar{W}'$ denotes the weight of a container for the TMVD system. Symbol $N'_{m,r}$ is the number of normal containers without the function of temperature control used for temperature range r food at period m. Symbol $\kappa'^{m,r}_{ijt}$ is a binary variable; if food i ordered by retailer j at time t is dispatched at period m, using a temperature range r vehicle, $\kappa'^{m,r}_{ijt} = 1$; otherwise, $\kappa'^{m,r}_{ijt} = 0$. Let $o'_{m,r}$ represent the fuel consumption rate (km/L) of a temperature range r vehicle under average vehicle payload and speed v_m, which is the road speed at period m. The fuel consumption for a temperature range r vehicle routing at period m can be calculated as $\left(2E(\Delta)\bar{n}'_{m,r} / n'_{m,r} + kn'_{m,r} / \sqrt{\sigma}\right)\Gamma'_{m,r}\ o'_{m,r}$. However, for the TMVD system, when vehicles stop at the terminal and retail stores to load and unload food, respectively, the engines still drive the compressors to maintain the temperature inside vehicles. Fuel consumption and refrigerant leakage during this process also produce greenhouse gas. Let both loading and unloading time for a normal container be h'. When the engine of a temperature range r vehicle drives only the compressor of the refrigeration unit without moving on the road, fuel consumption per unit time is o'^{0}_{r}. Thus, fuel consumption due to loading/unloading time in the TMVD system can be expressed as $\sum_m \sum_r 2h' N'_{m,r}\ o'^{0}_{r}$. Let the emission factor of unit fuel be α_{oil}. Thus, the total emissions from fuel consumption for the TMVD system, G'_{oil}, are given by

$$G'_{oil} = \sum_m \sum_r \left[\left(2E(\Delta)\bar{n}'_{m,r} / n'_{m,r} + kn'_{m,r} / \sqrt{\sigma}\right)\Gamma'_{m,r}\ o'_{m,r} + 2h' N'_{m,r}\ o'^{0}_{r}\right]\alpha_{oil} \tag{4-6}$$

Emissions from refrigerant leakage in the TMVD system

For the TMVD system, refrigerant leakage is from the refrigeration units in vehicles. As such, leakage depends on vehicle operating time; that is, vehicle routing and loading/unloading time. Let v_m be road speed at period m. Total vehicle routing time of a temperature range r vehicle at period m can be expressed as $\left[2E(\Delta)n'_{m,r}/\bar{n}'_{m,r}+kn'_{m,r}/\sqrt{\sigma}\right]/v_m$. Furthermore, the emissions from refrigerant leakage in the TMVD system, $G'_{refrigerant}$, can be calculated as

$$G'_{refrigerant}=\sum_m\sum_r\left[\left(2E(\Delta)\bar{n}'_{m,r}/n'_{m,r}+kn'_{m,r}/\sqrt{\sigma}\right)/v_m+2h'N'_{m,r}\right]K'_r \tag{4-7}$$

where K'_r represents the emissions from refrigerant leakage per unit operating time of a temperature range r vehicle. The method for estimating K'_r is described in Section 4.2.3.

4.2.3 Method to estimate refrigerant leakage

For temperature-controlled food, which needs refrigeration equipment to maintain temperature during transport, refrigerant leakage into the environment produces greenhouse gas. According to IPCC (2006), the methods to estimate emissions from refrigerant leakage include the mass-balance approach and the emission factor approach. The mass-balance approach relies on knowledge of the annual sales of refrigerant, refrigerant destroyed, and any charges in equipment stock that occur on a sub-application basis. Therefore, the mass-balance approach is suitable for refrigeration equipment firms but not suitable for carriers who do not manufacture refrigeration equipment. For this reason, this dissertation chose the emission factor approach to estimate emissions from refrigerant leakage. According to IPCC (2006), for emission factor approach, emissions from refrigerant leakage can be calculated using the following equation.

$$K_{year}=M*ALR*GWP \tag{4-8}$$

where K_{year} is the emissions from the annual refrigerant leakage of the equipment; it is in terms of CO_2e. Symbol M is the refrigerant charge in the equipment, and ALR is the annual refrigerant leakage rate of the equipment. Therefore, the annual refrigerant leakage of the equipment can be expressed as $M * ALR$. GWP is the global warming potential of the refrigerant used by the equipment. Since refrigerant leaks while equipment is operating, leakage is calculated based on operating time. Furthermore, emissions from temperature range r refrigerant leakage per unit time for the MTJD and TMVD systems, K_r and K'_r, can be calculated as the following equations.

$$K_r = \left(M^{MTJD} / g\right) * ALR^{MTJD} * GWP^{MTJD} / \eta \tag{4-9}$$

$$K'_r = M_r^{TMVD} * ALR_r^{TMVD} * GWP_r^{TMVD} / \eta' \tag{4-10}$$

where M^{MTJD}, M_r^{TMVD} and GWP^{MTJD}, GWP_r^{TMVD} represent the refrigerant charge and global warming potential of a MTJD freezer and a temperature range r vehicle, respectively. Symbol g denotes freezer capacity in terms of cold accumulators. Therefore, the refrigerant charge for a cold accumulator can be expressed as $\left(M^{MTJD} / g\right)$, and ALR^{MTJD} and ALR^{MTJD} denotes the annual refrigerant leakage rate of a freezer and a temperature range r vehicle, respectively. Symbols η and η'_r represent the annual average operating time of the freezer and temperature range r vehicle, respectively.

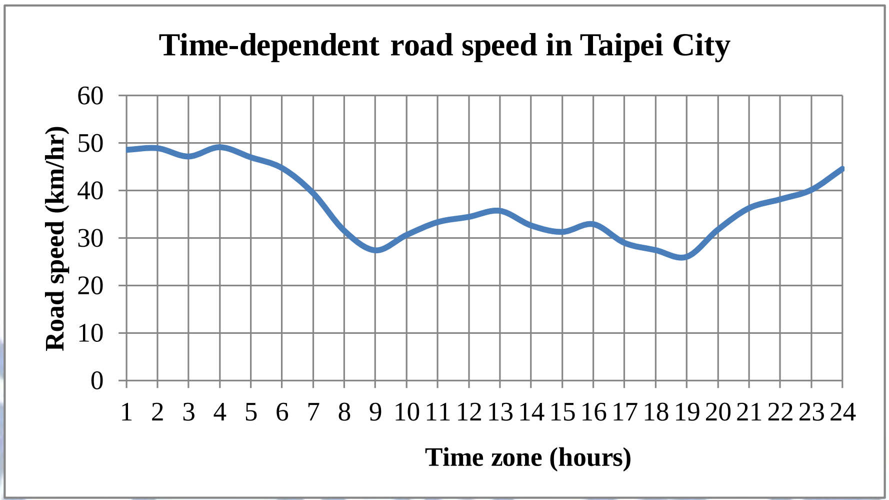
Algorithm

This chapter solves the optimal delivery scheduling by the algorithm described in Section 3.3, for the MTJD and the TMVD system, respectively. Then, this chapter calculates the emissions under the optimal delivery scheduling for the two systems to analyze and compare them.

4.3 Case Study

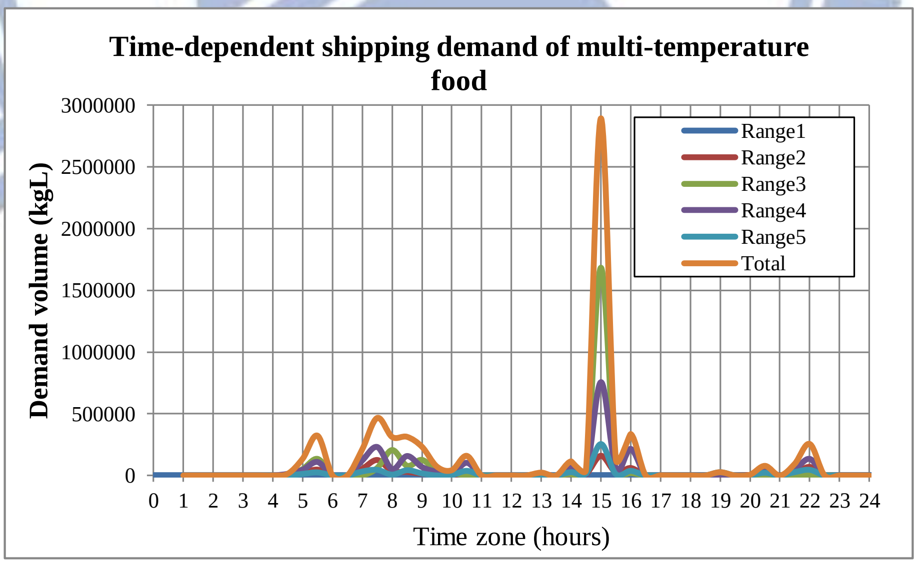
In this section, a numerical example is presented to demonstrate the application of the proposed model. Following Chapter 3, the example covered an area of 500 square kilometers and comprised an extraction of the customer characteristics that included time window constraints and shipping demand. Road speeds varying with times in the study area are shown in Figure 4-4. In this case, the carrier receives 1177 orders for 20 kinds of food from 85 different retailers. The food is divided into five different ranges, as shown in Table 4-1. Base values for parameters related to vehicles and refrigerants were estimated by data collection and interviewing manufacturers of temperature-control equipment, as listed in Table 4-2.

This dissertation assumes one operating day, namely 24 hours, as the entire study period, with the unit of time for the study being one hour. The temporal pattern of demand during the entire study period is shown in Figure 4-5. Demand time is approximated as the middle of a time window, demand volume is calculated in terms of kgL, and it should be noted that there is a difference in peaks for different temperature range food. Retailer demand for most temperature range food peaks from 7:00-9:00 and 14:00-16:00 because retailers 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 time. As for the differences among the five ranges, Range 3 has the most demand volume because this range contains the majority of perishable food in the example. Demand for Range 1, which consists of only sashimi, is most centralized due to its shortest shelf life time and because it is affected by temperature much more than other food.



Source: This dissertation.

Figure 4- 4 Time-dependent road speed in Taipei City



Source: This dissertation.

Figure 4- 5 Time-dependent demand for different temperature range food

Table 4- 1 Initial values for food demand

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~-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~+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~+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~)	18	Chocolate	0.3	0.132	0.440
	19	Cookie	1.2	0.170	0.142
	20	Soft drink	1.2	1.120	0.933

Source: This dissertation.

Table 4- 2 Value of parameters related to vehicles and refrigerants

Definition		Value
Fuel consumption rate of refrigerated vehicle (L/km)		0.10566
Fuel consumption rate of refrigerated vehicle as loading/unloading food (L/minute)		0.0147
Fuel consumption rate of regular vehicle (L/km)		0.09434
Loading or unloading time per container of TMVD system (minute)		1
Loading or unloading time per cold box of MTJD system (minute)		1
Refrigerant category and charge of refrigerated vehicles (kg)	Range 1	R404, 1.2
	Range 2	R134, 1.0
	Range 3	R134, 1.0
	Range 4	R134, 1.0
	Range 5	0
Refrigerant category and charge of freezer in MTJD system (kg)		R507, 3
Freezer capacity of MTJD system (cold accumulators)		78
Annual leakage rate of refrigerants in refrigerated vehicles		30%
Annual leakage rate of refrigerants in freezers		5%
Number of cold accumulators used for a cold box for temperature Ranges 1, 2, 3, 4, 5 (cold accumulators)		6, 6, 6, 4, 0
Capacities of a refrigerated or regular vehicle (m^3)		16
Capacity of a cold box of MTJD system (L)		300

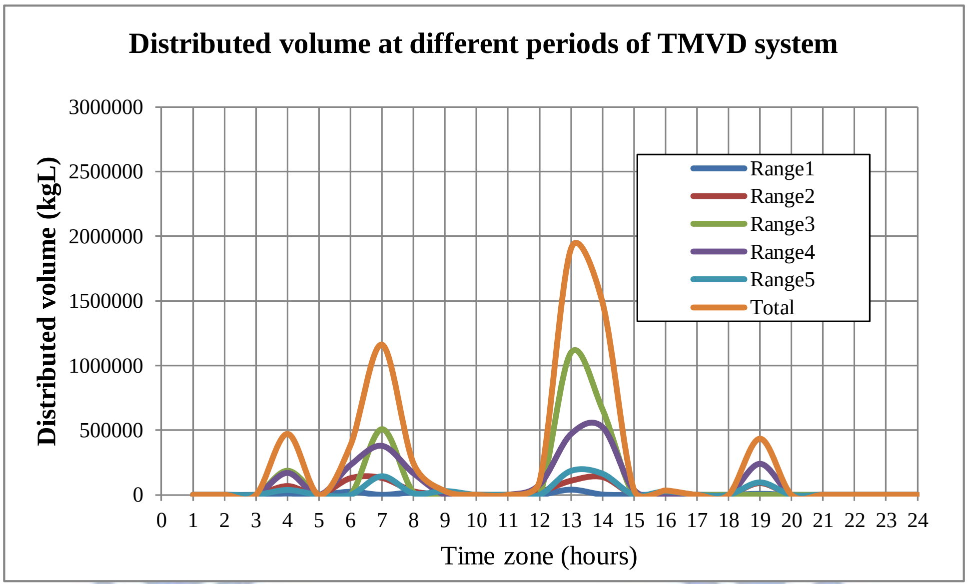
Source: This dissertation.

4.3.1 Distributed volume under minimizing delivery costs

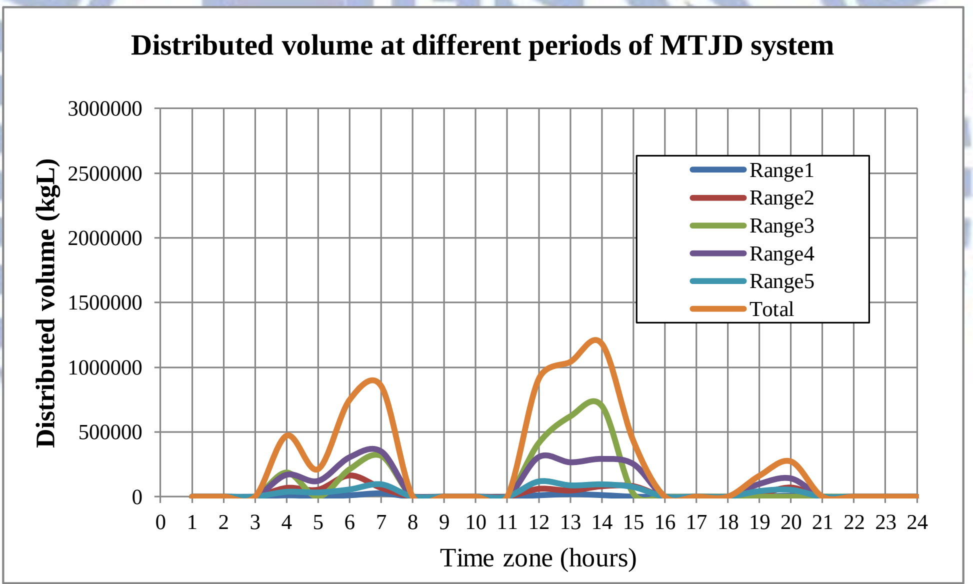
With the objective of minimizing delivery costs, the delivery schedule (i.e., optimal distribution time for each order of food) can be solved by the model and algorithm in Section 3.2.2 and Section 3.3, respectively. However, Section 3.2.2 did not take the impact of vehicle payload on fuel consumption into account. This chapter further modifies the delivery-scheduling model with the payload function developed in Section 4.1. Figures 4-6(a) and (b) show the temporal patterns of distributed volume for different temperature ranges under minimized delivery costs in the TMVD and MTJD systems, respectively, in terms of kgL. The figures show that time-dependent demand for different temperature ranges can be smoothed. Furthermore, the figures show the TMVD system distributes more food than the MTJD system at 7:00, 8:00, 9:00, 13:00, 14:00, 16:00, and 19:00. At 7:00, for TMVD system, the distributed volumes of Range 2, 3, 4 and 5 foods are greater than those for the MTJD system. If those Range 2, 3, 4 and 5 foods were distributed at 6:00, as with the MTJD system, more refrigerated vehicles would be used with lower capacity utilization because the vehicle capacity of the TMVD system is much larger than cold boxes capacity of the MTJD system. Therefore, in the TMVD system, food should be mass distributed so capacity utilization can be maximized.

However, the MTJD system with its joint delivery feature can distribute different temperature food at earlier periods but still within the time windows. For the same reason, some food distributed at 12:00 or 15:00 in the MTJD system are transported at 13:00-14:00 in the TMVD system, and the TMVD system mass transports food at 19:00, which is distributed from 19:00-20:00 in the MTJD system. In sum, the TMVD system consolidates and masses food within the same range to deliver at fewer periods, thus the temporal patterns of distributed volume for all temperature ranges are similar. As for the MTJD system, since it has the flexibility by using cold boxes, the differences among temporal patterns of distributed volume for different temperature ranges are more marked and match time-dependent demand patterns. In practice, uncertainty of demand makes delivery scheduling difficult. Time-varying demand results in huge differences in equipment usage during different periods. However, using the MTJD technique, carriers can deal with time-dependent demand by jointly distributing. Thus, the difference between periods in distributed volumes and equipment usage can be both reduced.

On the other hand, vehicle speed in urban areas is influenced by traffic volume and other factors, such as weather and accidents. This dissertation deals with the uncertainty of traffic congestion through the same method used for time-dependent demand. That is, by dividing the study duration into many small periods, the time-varying road speed can then be reflected not only in scheduling but also in emissions estimations. As shown in Figure 4-4, the road speed at 19:00 is lower than at 20:00. The lower road speed results in a higher fuel consumption rate, as shown in Eq. (4-1). Comparing the distributed volume of the two systems at 19:00 and 20:00, the TMVD system transports more food than MTJD at 19:00 for all temperature ranges, but it does not dispatch at 20:00. The reason for this is that the carrier needs to accumulate food volume to enhance economies of scale. However, if the carrier distributes all the food at 20:00, penalty costs due to late delivery increase. On the other hand, the MTJD system disperses this food at 19:00 and 20:00. This indicates that the flexibility of the MTJD system helps carriers reduce distributed volume at higher traffic congestion periods if such adjustments do not cause late delivery. Thus, fuel consumption due to traffic congestion can be reduced.



(a) TMVD system



(b) MTJD system

Source: This dissertation.

Figure 4- 6 Time-dependent distributed volume

4.3.2 Emissions under minimizing delivery costs

Table 4-3 shows the emissions of the TMVD and MTJD systems under the distributed volume pattern in Figures 4-6 (a) and (b), respectively. It is clear from the figures that emissions from fuel consumption are very high as compared to other sources of emissions. This is due to considerable vehicle routing distances during transport for both systems. Table 4-3 shows the TMVD system results in much higher emissions from fuel consumption than the MTJD system during most periods. This is because the fuel consumption rates of refrigerated vehicles in TMVD are higher than the regular vehicles in the MTJD system. In addition, the TMVD system cannot deliver different temperature range foods jointly using a single vehicle. For retailers who order more than one temperature range food, the TMVD system dispatches more than one vehicle; thus, the total vehicle routing distance increases markedly. This implies that carriers should use the MTJD system to reduce routing distances and emissions simultaneously. However, at 5:00, 6:00, 12:00, 15:00, and 20:00, the emissions from fuel consumption in the MTJD system exceeds that of the TMVD system. That is because, at these periods, the distributed volume of MTJD is at least twice that of the TMVD system.

Regarding the emissions due to refrigerant leakage, Table 4-3 shows that emissions from refrigerant leakage using the MTJD system are higher than in the TMVD system at most periods. However, at 8:00, 16:00, and 19:00, the TMVD system yields higher emissions from refrigerant leakage than the MTJD system because MTJD does not distribute any food at 8:00 and 16:00. At 19:00, the food distributed by using the MTJD system is about one-third that of the TMVD system. Overall, emissions from refrigerant leakage account for low percentages of the total emissions in both systems when compared to fuel consumption. As for emissions from electric power consumption, as shown in Table 4-3, those are extremely low when compared to emissions from fuel consumption. Even for the period with most emissions from electric power consumption, 14:00, emissions from the MTJD system at this period are still less than the TMVD system. Similarly, emissions from fuel consumption during loading/unloading time in the TMVD system have little influence on total emissions.

In sum, considering total emissions from the two systems, except for the periods when distributed volume of MTJD exceeds TMVD, such as 5:00, 6:00, 12:00, 15:00, and 20:00, emissions from the MTJD system are less than the TMVD system.

GHG emissions of logistics systems depend on distributed volume and vehicle speed, as shown in the equations in this chapter. Therefore, there exists uncertainty of emissions due to factors like time-varying demand and traffic congestion. For the TMVD system, as shown in Table 4-3, emissions at 13:00 are lower than that at 14:00, although the distributed volume at 13:00 is much higher than that at 14:00, as shown in Figure 4-6. This is because the road speed at 14:00 is slower than that at 13:00 due to increased congestion, as shown in Figure 4-4. This result shows that emissions are affected not only by time-dependent demand but also by dynamic levels of traffic congestion. As for the MTJD system, during each distribution peak, such as 6:00-7:00 and 12:00-14:00, the emissions at different periods are close when compared with the TMVD system. This implies that MTJD reduces not only total emissions but also the uncertainty of emissions by joint delivery.

Table 4- 3 Emissions from TMVD and MTJD systems

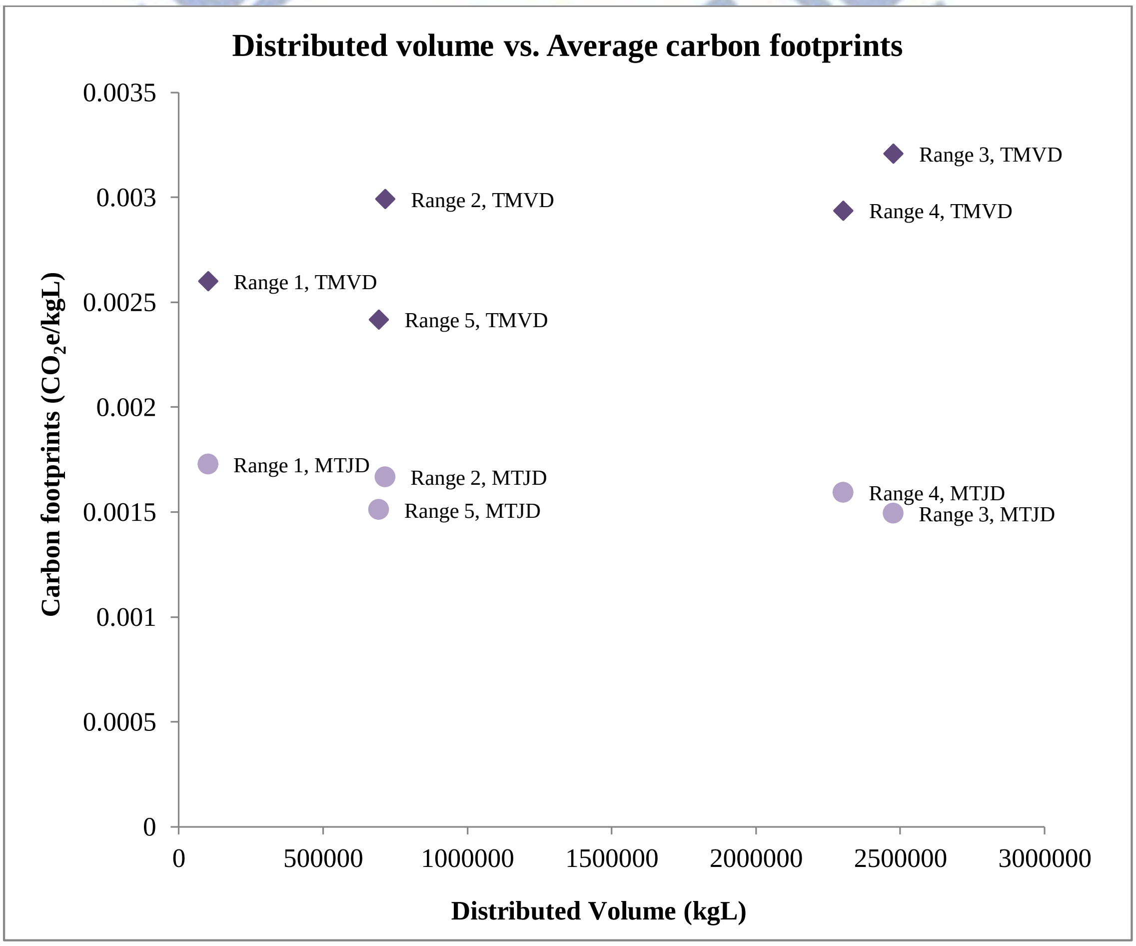
(unit: $kgCO_2e$)

	MTJD system				TMVD system			
Source of emissions /Time	Fuel consumption	Electric power consumption	Refrigerant leakage	Total	Fuel consumption		Refrigerant leakage	Total
					Routing	Loading/Unloading		
1:00	0	0	0	0	0	0	0	0
2:00	0	0	0	0	0	0	0	0
3:00	0	0	0	0	0	0	0	0
4:00	573.44	12.25	0.78	586.47	969.57	3.33	0.27	973.17
5:00	294.42	5.61	0.37	300.40	0	0	0	0
6:00	1722.30	21.51	1.37	1745.18	1108.40	7.49	0.22	1116.11
7:00	2036.40	20.34	1.31	2058.05	5146.30	0	0.45	5146.75
8:00	0	0	0	0	616.59	5.55	0.18	622.32
9:00	0	0	0	0	12.55	0	0	12.55
10:00	0	0	0	0	0	0	0	0
11:00	0	0	0	0	0	0	0	0
12:00	1814.80	20.56	1.33	1836.69	154.93	0	0.09	155.02
13:00	923.40	25.47	1.62	950.49	4638.10	12.76	0.76	4651.62
14:00	1262.50	29.12	1.85	1293.47	5457.60	0.83	0.62	5459.06
15:00	638.09	9.18	0.62	647.89	20.11	0	0.04	20.16
16:00	0	0	0	0	32.81	0	0.04	32.86
17:00	0	0	0	0	0	0	0	0
18:00	0	0	0	0	0	0	0	0
19:00	96.07	2.74	0.19	99.01	593.95	2.50	0.22	596.67
20:00	255.30	7.04	0.45	262.79	0	0	0	0
21:00	0	0	0	0	0	0	0	0
22:00	0	0	0	0	0	0	0	0
23:00	0	0	0	0	0	0	0	0
24:00	0	0	0	0	0	0	0	0
Total	9616.72	153.82	9.88	9780.42	18750.92	32.46	2.89	18786.27

Source: This dissertation.

4.3.3 Carbon footprints of delivering multi-temperature food

In practice, many retailers ask suppliers to provide information about carbon footprints of products. Figure 4-7 shows the relationship between total distributed volume and average carbon footprints of food due to delivery by the TMVD and MTJD systems. Average carbon footprints of food are calculated by dividing total emissions by total distributed volume in terms of kgL, for each temperature range. Figure 4-7 shows the MTJD system causes smaller carbon footprints per unit cargo than the TMVD system for all temperature ranges. The reason for this is that the MTJD system reduces emissions from fuel consumption, which is the main source of emissions for both systems, as discussed earlier. This implies that the MTJD system not only reduces emissions for food delivery, but also enhances the sustainability of merchandise.



Source: This dissertation.

Figure 4- 7 Distributed volume vs. average carbon footprints

Carbon footprints of the MTJD system

As for comparison of carbon footprints among the ranges in the MTJD system, Range 1 and Range 2 foods yield the largest carbon footprints. Moreover, Range 4 and Range 5 result in the third and fourth largest carbon footprints, respectively. Range 3 food yields the smallest carbon footprint among the five ranges. The reasons for the rankings are as the follows. First, in the MTJD system, Ranges 1, 2, and 3 use more cold accumulators per cold box than Range 4, as shown in Table 4-2. Therefore, not only electric power but also fuel consumption rates of the Range 1–3 cold boxes are higher than for Range 4 due to lower temperature ranges and the weight of more cold accumulators. Second, the distributed volume of Range 3 is much greater than other ranges. In the MTJD system, fuel consumption is shared among all temperature ranges, using percentage of total distributed volume. For each range, if the volume increases by one unit at a time, while other ranges remain constant, the percentage of the total distributed volume due to that range adding one unit is actually reduced. For instance, assume the distributed volume of each range is 100 initially, and the volume of Range 1 increases 10 units at a time. Table 4-4 shows the variation of percentage accounted for by Range 1 in this instance. The increased percentage accounted for by Range 1 due to adding 10 units is shown in the rightmost column. As shown in Table 4-4, the greater the distributed volume, the lower the increase in percentage when volume goes up. Since fuel consumption depends on the percentage a given temperature range food accounts for, the lower the increased percentage, thus the lower the fuel consumption and the lower the increased GHG emissions from fuel. Therefore, in the MTJD system, there exists economies of scale in the relationship between distributed volume and carbon footprints. As such, although Range 3 food is heavier than other food ranges, the carbon footprints for this food range are the smallest because it has the largest distributed volume. That is, in the MTJD system, the higher the distributed volume, the smaller the carbon footprints, and the lower the external cost to the environment per unit food. This implies that large size carriers should use the MTJD technique to reduce carbon footprints and external costs related to the environment.

Table 4- 4 Instance for illustrating changes in distributed volume

Distributed volume of Range 1 food	Total distributed volume of five ranges food[1]	Percentage of Range 1 food accounts for total distributed volume	Increased percentage due to adding 10 units Range 1 food
100	500	20.000%	/
110	510	21.569%	1.569%
120	520	23.077%	1.508%
130	530	24.528%	1.451%
140	540	25.926%	1.398%
150	550	27.273%	1.347%
160	560	28.571%	1.299%
170	570	29.825%	1.253%
180	580	31.034%	1.210%
190	590	32.203%	1.169%
200	600	33.333%	1.130%
210	610	34.426%	1.093%

[1]The distributed volumes of Ranges 2, 3, 4, and 5 are 100 units each.
Source: This dissertation.

Carbon footprints of the TMVD system

Ranking the temperature ranges according to average carbon footprints in the TMVD system, Range 3 food yields the highlight carbon footprints due to the delivery unit of food (kgL). Moreover, Range 2 and Range 4 result in the second and third high carbon footprints (CO_2e/kgL), respectively, while Range 1 and Range 5 foods yield lower carbon footprints than other three ranges. The reasons for this ranking include the following. First, in the TMVD system, fuel consumption accounts for highest percentage among all emission sources. Since fuel consumption rate depends on food weight, the heaviest food, Range 3, naturally results in biggest carbon footprints. Second, comparing Range 2 with Range 4, the carbon footprints of these two ranges are very close. Although the total distributed volume and weight of Range 4 foods are higher than for Range 2, the volume of each order for Range 2 is much smaller than for Range 4, which includes huge size drinks. The distributed volume of Range 2 food is dispersed among more retailers than Range 4. Increased stopping locations yields longer routing distances, and results in more fuel consumption and GHG. Third, in the TMVD system, temperature control relies on vehicle engines and raises fuel consumption rates of vehicles. Therefore, although Range 1 food is the lightest among all temperature ranges, the carbon footprints for Range 1 are still larger than Range 5 food, which is stored at a constant temperature and consumes no energy due to temperature control. The above discussion implies that, in the TMVD system, carbon footprints mainly depend on density and temperature range of food. The influence of total distributed amount on average carbon footprints is not noticeable. The reason for this is that TMVD aims to mass food to distribute so as to enhance economies of scale, as mentioned earlier. Since total distributed volume is large, the influence due to differences in distributed volume decreases. That is, the higher the denominator, the lower the value variation due to changes in the numerator. These results further imply that carriers should reduce emissions due to delivering heavy and low-temperature food needed by many different retailers with priority if carriers use the TMVD system. This would enhance the efficiency of GHG reduction, and the larger carbon footprints of such food would decrease.

Difference in carbon footprints of the two systems

Furthermore, this dissertation compares the differences in carbon footprints between the TMVD and MTJD systems. Figure 4-7 shows the difference for Range 3 food is the greatest, among the five ranges, followed by Range 4, Range 2, Range 5, and Range 1, respectively. Given this, the higher the distributed volume (kgL), the greater the difference in carbon footprints between the two systems. This is because the MTJD system yields smaller carbon footprints per unit food than the TMVD system for all temperature ranges, and makes carbon footprints decrease by a greater percentage than distributed volume raises. That is, the higher the distributed volume, the more the MTJD system can reduce the carbon footprints per unit food, which implies that the larger the carrier size, the greater the benefit to carbon footprint reduction per unit food by using MTJD.

4.4 Summary

In sum, this chapter aims to formulate mathematical models to estimate and compare emissions from traditional multi-vehicle delivery and multi-temperature joint delivery systems for food. A numerical example illustrates the application of the proposed models and compares the emissions for each period of the two systems under conditions of minimized delivery costs. The proposed model can analyze the uncertainty of dynamic demand, levels of traffic congestion, and emissions.

The results indicate that, as compared to the TMVD system, the MTJD system yields less total emissions by lowering fuel consumption even when it generates more CO_2e due to refrigerant leakage and electric power consumption for freezers. The results suggest carriers should use the MTJD system to reduce routing distances and emissions simultaneously. This chapter further analyzes the carbon footprints per unit of food from the MTJD and TMVD systems. The results show that there exists economies of scale in the relationship between distributed volume and carbon footprints in the MTJD system, but in the TMVD system, the influence of distributed volume on average carbon footprints is not noticeable. Research related to carbon footprint reduction per unit of food is useful for carriers, retailers, and suppliers in the whole supply chain.

Chapter 5 Optimal delivery scheduling for multi-temperature food delivery under carbon tax

This chapter explores the optimal delivery scheduling in the MTJD system under the assumption that the carrier is levied carbon tax. The reminder of this chapter is organized as follows. Section 5.1 statements the studied problem of this chapter. Section 5.2 formulates the food departure time determining model with emissions cost for MTJD system. A numerical example illustrates the application of the models in Section 5.3. Finally, a short summary is provided in Section 5.4.

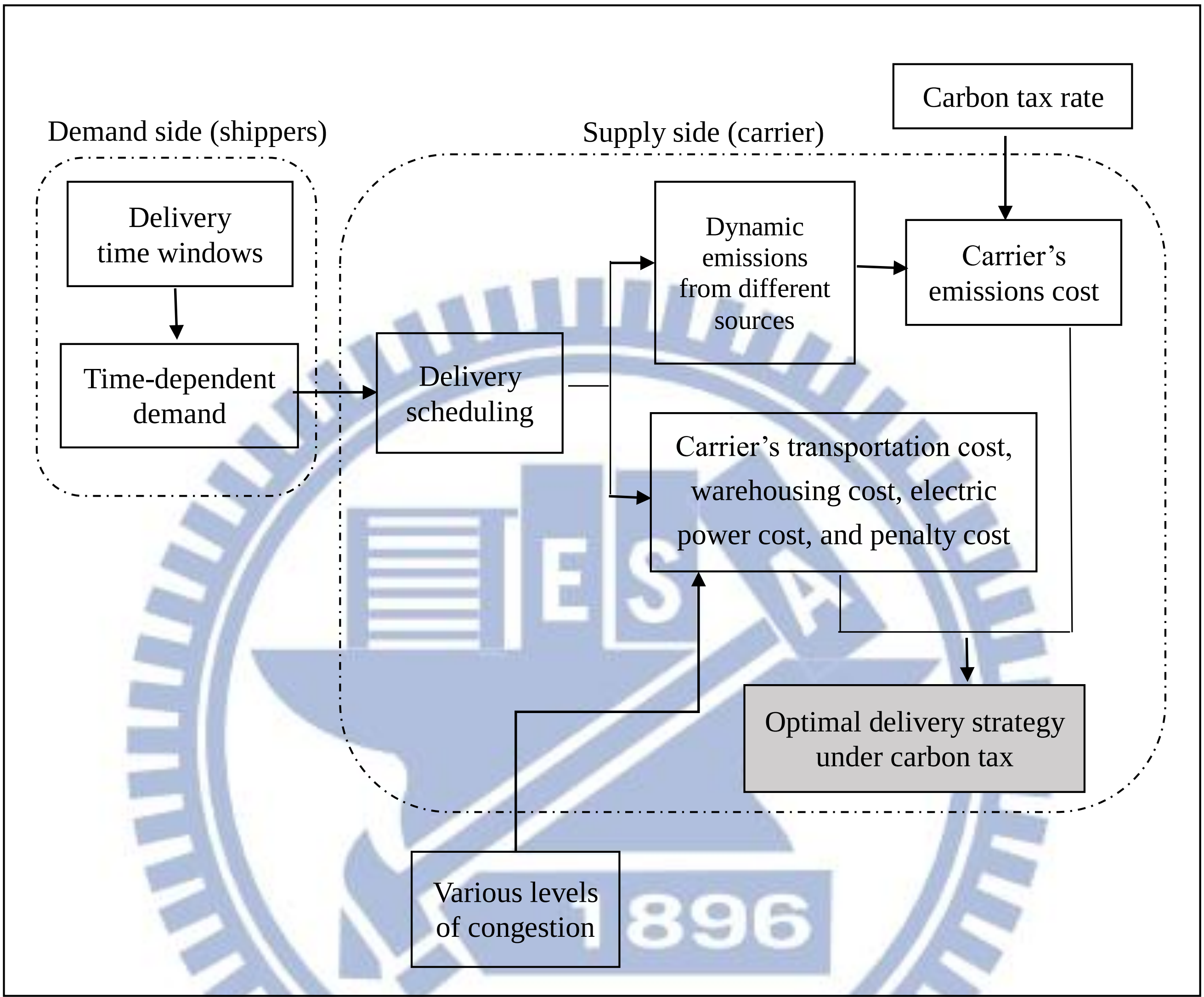
5.1 Introduction to the problem

Delivery scheduling is a prerequisite for a carrier's operations. For multi-temperature joint delivery (MTJD) system, delivery scheduling is an extremely complex task, largely owing to various temporal demand patterns for multi-temperature ranges food and delivery time windows set by shippers. As discussed in Chapter 1, the MTJD technique can deliver more than one temperature range food simultaneously in a single regular vehicle. It utilizes replaceable cold accumulators of different temperatures and sizes in standardized cold insulated boxes to maintain precise temperatures. However, delivering multi-temperature food contributes a considerable amount of greenhouse gas emissions due to fuel burn and HFCs and PFCs generated by refrigeration equipment. Since many governments around the world have developed futures markets for emission allowances or levied carbon tax, how to deliver multi-temperature food under emissions cost has become an importation issue for carriers, as discussed in Chapter 4. Therefore, this chapter aims to optimize the delivery scheduling for the MTJD system, taking into account delivery and emissions cost simultaneously.

This chapter formulates a delivery scheduling programming model under carbon tax, based on the cost functions in Section 3.2.2 and emissions estimation functions in Section 4.1, with a carbon tax rate. Then, the optimal delivery list at each period under minimized costs and carbon tax can be determined.

Assumption

In this chapter, the decision maker is a carrier who uses the MTJD technique and has to schedule daily delivery, taking into account delivery cost and emissions cost due to carbon tax. Figure 5-1 shows the framework of this chapter. This chapter follows the former chapters to divide the entire study duration into many periods. The delivery cost of the carrier contains warehousing cost, transportation cost, electric power cost, and penalty cost, as Section 3.2.2. However, Section 3.2.2 does not consider the influence of payload, i.e., weights of food and cold boxes. In Chapter 5, the influence of payload on consumption rate is taken into account. Thus, this chapter can calculate the related cost more precisely than Chapter 3. For routing issue, this chapter only explores the scheduling problem by continuous approximation (Daganzo, 1999). The vehicle routing problem is not solved in this chapter. The emissions cost is the product of carbon tax rate and emissions volume which is in terms of CO_2e. As discussed in Chapter 4, the sources of emissions in the MTJD system include fuel consumption of vehicle and electric power consumption and refrigerant leakage of freezers. As for the emissions from the warehouse, the energy consumption and refrigerant leakage at the warehouse are not affected by the results of delivery scheduling because the refrigeration equipment at the warehouses operates all the time. As above-mentioned components, there are a lot of variables in the problem. To simplify the problem and solve it in limited time, the demand-supply interaction between the carrier and shippers is not taken into account in this chapter.



Source: This dissertation.

Figure 5- 1 The framework of Chapter 5

5.2 Model formulation

This section describes a mathematical programming model for determining the optimal departure time from terminal for each order of multi-temperature food, considering delivery and emissions cost and assuming the carrier is seeking to minimize total cost. The model is based on Section 3.2.2 and Section 4.1. In Section 3.2.2, this dissertation constructs a model to solve the optimal fleet size and food departure time for MTJD system. In Section 4.1, this dissertation formulates mathematical models to estimate emissions from multi-temperature joint delivery (MTJD) system for food. Furthermore, this chapter refers these two sections. The delivery cost and emissions cost functions of the MTJD system are as follows.

5.2.1 Delivery cost for the MTJD system

Dividing the entire study duration into many small periods, the delivery cost for multi-temperature food delivery can be formulated as follows. The costs considered for multi-temperature logistics are warehousing cost, transportation cost, electric power cost and penalty cost. Warehousing costs are time cost and storage cost for food in terminal. Transportation cost is related to vehicles usage and operating. Electric power cost is spent for controlling food temperature during the transit process. Finally, penalty cost exists when the delivery time window is violated.

Let y_{ijt}^{s} denote the time that food i ordered by retailer j at time t leaves terminal. The purpose of the model of this study is to find the optimal departure time for each order of food (i.e., $y_{ijt}^{s}, \forall i, j, t$) by minimizing the carrier's cost. The cost functions formulation are as follows.

The warehousing cost includes the costs for food storage and temperature control in the terminal. Let y_{ijt}^{f} and q_{ijt} denote the time and quantity that food i ordered by retailer j at time t arrives at the terminal, respectively. Symbol B_i represents the warehousing 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. Let V_i denote the volume of unit food i. Hence, the total warehousing cost, C_{War}, can be formulated as

$$C_{War} = \sum_i \sum_j \sum_t q_{ijt} V_i \; B_i \left(y_{ijt}^{s} - y_{ijt}^{f} \right) \tag{5-1}$$

The transportation cost includes fixed and variable costs for using vehicles, and loading/unloading costs for cold boxes. 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 fuel consumption, and fuel consumption varies with routing distance. This dissertation calculates total vehicle travel distance by continuous approximation (Daganzo, 1999). 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 $\bar{D}_m$. Let σ represent 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.

However, expect for routing distance, the fuel consumption also depends on the vehicle payload and speed. Section 3.2.2 does not deal with the fuel consumption rate varying with payload. This chapter follows Section 4.1 to refer Suzuki (2011) to analyze the influence of payload on fuel consumption rate. Let symbol Γ_m represent the average vehicle payload factor at period m that measures the deviation of a vehicle's fuel consumption rate from the average value based on the payload. Let Φ denote the average payload in the long run of the MTJD system. Thus, Γ_m can be expressed as

$$\Gamma_m = \left(\sum_i \sum_j \sum_t \kappa_{ijt}^m q_{ijt} W_i + \overline{W}_r N_{m,r} \right) / \Phi \tag{5-2}$$

where W_i is the weight of unit food i, and $\overline{W}_r$ denotes the weight of a cold box of the MTJD system, which includes weight of the box and cold accumulators. Symbol $N_{m,r}$ represents the number of used cold boxes for temperature range r food at period m. Symbol κ_{ijt}^m is a binary variable; if food i ordered by retailer j at time t is dispatched at period m, $\kappa_{ijt}^m = 1$; otherwise, $\kappa_{ijt}^m = 0$. Let o_m represent the fuel consumption rate (km/L) of a vehicle under average vehicle payload and speed v_m, which is the road speed at period m. Thus, the fuel consumption of the MTJD system at period m can be calculated as $\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m$. Let the cost per unit fuel consumption be O. The fuel cost at period m can be calculated as $\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m O$.

The loading/unloading costs depend on the number of cold boxes used for delivery. Let δ^1 represent the loading/unloading costs for a cold box, then the loading/unloading cost at period m can be expressed as $\delta^1 N_{m,r}^1$, and the total loading/unloading costs during the entire study duration can be shown as $\sum_m \sum_r \left(\delta^1 N_{m,r}\right)$. Thus, the total transportation cost, C_{Tra}, can be formulated as

$$C_{Tra} = \sum_m \left[a_m f + \left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right]\Gamma_m o_m O + \sum_r \left(\delta^1 N^1_{m,r}\right)\right] \tag{5-3}$$

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

$$C_{Ene} = \sum_m \left(\phi^1_r N^1_{m,r}\right)\left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right] / v_m \tag{5-4}$$

where ϕ^1_r denotes the electric power cost of a cold box for storing temperature range r food per unit time.

The numbers of cold boxes 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 dissertation 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^1 denote the capacity utilizations of cold boxes. Symbol V^1 denotes the capacity of a cold box, and the constraint related to cold boxes can be constructed as

$$\gamma^1 N^1_{m,r} V^1 \geq \sum_i \sum_j \sum_t \theta^m_{ijt} q_{ijt} V_i \qquad \forall m, r \tag{5-5}$$

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'^{1} denote the volume of a cold box; γ^{3} denotes the capacity utilizations of vehicle. Symbol V^{1} denotes the capacity of a cold box. Thus, the constraint related to fleet capacity and cold box usage can be expressed as

$$\sum_{r}\left(N_{m,r}^{1}V'^{1}\right)\leq\gamma^{3}\chi\Omega \quad \forall m \tag{5-6}$$

where Ω and χ denote the number of vehicles and the capacity of unit vehicle, respectively.

Regarding the penalty cost, according to Hsu et al. (2007), 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

$$C_{Pen} = \sum_{m}\sum_{i}\sum_{j}\theta_{ijt}^{m} b_{ijt} q_{ijt} P_i d_{ij} \left[\lambda\left(y_{ijt}^{s} + \rho_m - s_{ijt}\right)\right]^{\zeta_i} \tag{5-7}$$

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 dissertation calculates vehicle travel time at period m, ρ_m, using continuous approximation (Daganzo, 1999), as mentioned earlier. Furthermore, the number of vehicles used at period m can be estimated as $\left(n_m \bar{D}_m\right)/\bar{L}_m$ 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 discussed earlier in the section of transportation cost calculation. The ρ_m can be expressed as

$$\rho_m = \frac{2E(\Delta)n_m / \bar{n}_m + kn_m / \sqrt{\sigma}}{v_m\left(n\bar{D}_m / \bar{L}_m\right)} \tag{5-8}$$

Furthermore, ρ_m can be simplified as

$$\rho_m = \left[2E(\Delta) + k\bar{n}_m / \sqrt{\sigma}\right] / v_m \tag{5-9}$$

5.2.2 Emissions cost from the MTJD system

This section describes the emission estimation model for the MTJD system based on the model developed in Section 4.1. As discussed earlier, the sources of emissions in the MTJD system contain fuel consumption due to vehicle routing, electric power consumption of freezers, and refrigerant leakage of freezers.

Similar with Section 4.1, this chapter focuses on the emissions due to transporting temperature-controlled food from the terminal to retailers. We focus on the emissions during the “delivery” process. The emissions due to food storage at warehouses are not considered since the refrigeration system at the warehouse operates all time. In such condition, both the energy consumption and refrigerant leakage from the warehouse is not affected by delivery scheduling. In addition, in the MTJD system, the emissions from the fuel consumption of vehicles only depend on routing but not on loading/unloading time because food is stored in cold boxes with replaceable cold accumulators to control temperature. Furthermore, the emission estimation method for each source is formulated as follows.

According to IPCC (2006), emissions from road transportation can be calculated by multiplying fuel consumption with a CO_2 emission factor. As mentioned in the discussion for transportation cost, the fuel consumption of the MTJD system at period m can be calculated as $\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m$. Thus, the emissions due to vehicle routing of the MTJD system, G_{oil}, are given by

$$G_{oil} = \sum_m \left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m \alpha_{oil} \tag{5-10}$$

For electric power consumption of freezers at the terminal, as discussed earlier, the freezers are used for accumulating cold to cold accumulators. Therefore, the electric power consumption depends on the number of used cold accumulators. On the other hand, the electric power consumption also depends on the usage time of cold accumulators. Since cold accumulators are used for temperature control during transport process, the usage time of cold accumulators can be calculated as the sum of vehicle routing and loading/unloading time. Let the loading and unloading time for one cold box be both h. The usage time of range r cold accumulators at period m can be expressed as $\left[\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m\right] + 2hN^1_{m,r}$. Let X_r be the number of cold accumulators used for one temperature range r cold box. Furthermore, the number of used cold accumulators for temperature range r food at period m can be calculated as $N^1_{m,r} X_r$, and the emissions from electric power consumption of MTJD system, $G_{electricity}$, can be expressed as

$$G_{electricity} = \sum_m \sum_r \left(N^1_{m,r} X_r\right)\left(\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m + 2hN^1_{m,r}\right) e\alpha_{electricity} \tag{5-11}$$

where e is the electric power consumption per unit time, unit cold accumulator; symbol $\alpha_{electricity}$ is the emission factor of unit electric power consumption.

Regarding emissions from refrigerant leakage, for the MTJD system, the refrigerant is inside freezers installed at terminals, and the leakage depends on the operating time of freezers. That is, the leakage depends on the time for accumulating cold, which depends on the usage time of cold accumulators, i.e., the sum of vehicle routing and loading/unloading time. Therefore, the emissions from the refrigerant leakage of MTJD system, $G_{refrigerant}$, can be calculated as

$$G_{refrigerant} = \sum_m \sum_r \left(N^1_{m,r} X_r\right)\left(\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m + 2hN^1_{m,r}\right) K_r \tag{5-12}$$

where K_r is the emissions from refrigerant leakage due to accumulating cold for a temperature range r accumulator per unit time, which is in terms of CO_2e. According to IPCC (2006), the annual emissions from refrigerant leakage can be calculated by the product of three parameters, which are annual refrigerant charge, annual refrigerant leakage rate of the equipment, and the global worming potential of the refrigerant. Let

M^{MTJD} represent the refrigerant charge of temperature range r freezers. Symbol g denotes the freezer capacity in terms of cold accumulators. Then, the refrigerant charge for a cold accumulator can be expressed as $\left(M^{MTJD}/g\right)$. Let ALR^{MTJD} denote the annual refrigerant leakage rate of freezer. Thus, the annual refrigerant leakage of the equipment can be expressed as $\left(M^{MTJD}/g\right)ALR^{MTJD}$. Furthermore, let η denote the annual average operating time of the freezer. Since the refrigerant leaks during equipment operating, the leakage can be calculated based on the operating time. The emissions from refrigerant leakage per unit time of MTJD system, K_r, can be calculated as

$$K_r = \left(M^{MTJD}/g\right) * ALR^{MTJD} * GWP^{MTJD}/\eta \tag{5-13}$$

where GWP^{MTJD} is the global worming potential of the refrigerant used by freezer.

Let Y denote the cost per unit emission, which is carbon tax in practice; the emissions cost of carrier can be expressed as $Y\left(G_{oil} + G_{electrity} + G_{refrigrant}\right)$.

5.2.3 Delivery scheduling model under carbon tax

This dissertation formulates a nonlinear programming problem here for determining the optimal departure time for each order of multi-temperature food by minimizing delivery and emissions cost subject to delivery time windows. Symbol Y denotes the cost for unit greenhouse gas emission. That is, carbon tax or price for emission allowance. According to the above discussion, the model combining delivery and emissions cost can be expressed as follows. The decision variable is the departure time for each order of food, y_{ijt}^{s}.

$$\underset{y^{s}_{ijt}}{Min} \quad C_{War} + C_{Tra} + C_{Ene} + C_{Pen} + Y\left(G_{oil} + G_{electrity} + G_{refrigrant}\right) \tag{5-14a}$$

$$C_{War} = \sum_{i}\sum_{j}\sum_{t} q_{ijt} V_i \; B_i \left(y^{s}_{ijt} - y^{f}_{ijt}\right) \tag{5-14b}$$

$$C_{Tra} = \sum_{m}\left[a_m f + \left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right]\Gamma_m o_m O + \sum_{r}\left(\delta^{1} N^{1}_{m,r}\right)\right] \tag{5-14c}$$

$$C_{Ene} = \sum_{m}\left(\phi^{1}_{r} N_{m,r}\right)\left[2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right] O / v_m \tag{5-14d}$$

$$C_{Pen} = \sum_{m}\sum_{i}\sum_{j} \theta^{m}_{ijt} b_{ijt} q_{ijt} P_i d_{ij} \left[\lambda\left(y^{s}_{ijt} + \rho_m - s_{ijt}\right)\right]^{\zeta_i} \tag{5-14e}$$

$$G_{oil} = \sum_{m}\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)\Gamma_m o_m \alpha_{oil} \tag{5-14f}$$

$$G_{electricity} = \sum_{m}\sum_{r}\left(N^{1}_{m,r} X_r\right)\left(\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m + 2hN^{1}_{m,r}\right) e \alpha_{electricity} \tag{5-14g}$$

$$G_{refrigerant} = \sum_{m}\sum_{r}\left(N^{1}_{m,r} X_r\right)\left(\left(2E(\Delta)\bar{n}_m / n_m + kn_m / \sqrt{\sigma}\right)/ v_m + 2hN^{1}_{m,r}\right) K_r \tag{5-14h}$$

$$\Gamma_m = \left(\sum_{i}\sum_{j}\sum_{t} \kappa^{m}_{ijt} q_{ijt} W_i \; + \overline{W}_r \; N_{m,r}\right) / \Phi \tag{5-14i}$$

$$\gamma^{1} N^{1}_{m,r} V^{1} \geq \sum_{i}\sum_{j}\sum_{t} \theta^{m}_{ijt} q_{ijt} V_i \qquad \forall m, r \tag{5-14j}$$

$$\sum_{r}\left(N^{1}_{m,r} V'^{1}\right) \leq \gamma^{3} \chi \Omega \quad \forall m \tag{5-14k}$$

$$\rho_m = \left[2E(\Delta) + k\bar{n}_m / \sqrt{\sigma}\right] / v_m \tag{5-14l}$$

$$K_r = \left(M^{MTJD} / g\right) * ALR^{MTJD} * GWP^{MTJD} / \eta \tag{5-14m}$$

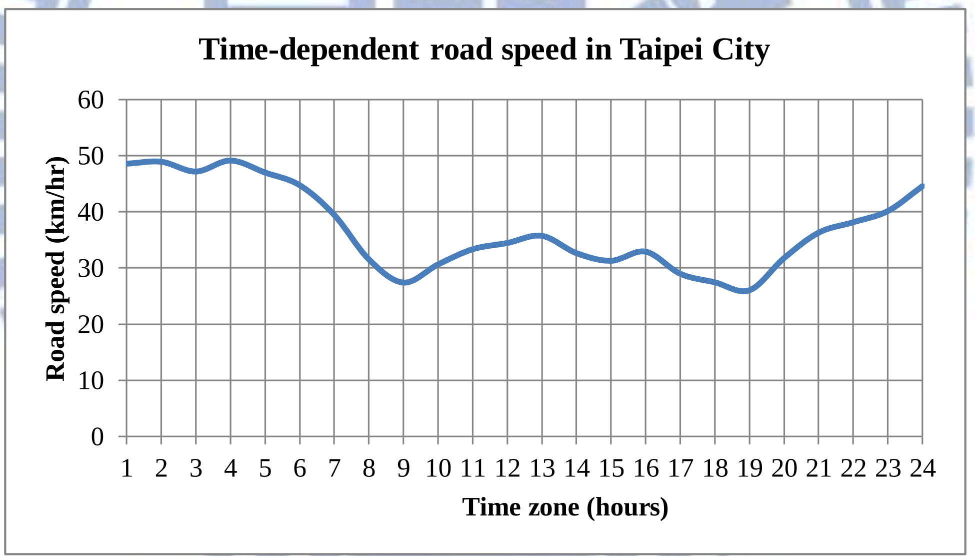
Eq.(5-14a) represents the objective function that minimizes delivery and emission costs through the study period, respectively. Eq.(5-14b), (5-14c), (5-14d) and (5-14e) define the warehousing, transportation, energy, and penalty cost as Eq. (3-7), (3-8), (3-11), and (3-12), respectively. Eq.(5-14f), Eq.(5-14g) and (5-14h) define the emissions from fuel consumption, electric power consumption, and refrigerant leakage as Eq. (4-2), (4-3), and (4-4), respectively. Eq. (5-14i) represents the payload factor estimation function as Eq. (4-1). Eq. (5-14j) constraints that the total capacity of cold boxes must be equal or larger than the total volume of shipments for each temperature range at each period. Furthermore, Eq. (5-14k) constraints the total volume of cold boxes at each period must be equal or smaller than the fleet capacity. Moreover, Eq. (5-14l) represents the travel time estimation function as Eq. (3-14). Eq. (5-14m) represents the refrigerant leakage estimation function as Eq. (4-9).

Algorithm

This chapter solves the optimal delivery scheduling under carbon tax levying, by the algorithm described in Section 3.3. However, in this chapter, the objective function and constraints are replaced with Eq. (5-14a)-(5-14m), as discussed earlier.

5.3 Case Study

This section presents a numerical example to demonstrate the application of the model combing delivery cost and emissions cost for the MTJD system. Following the former chapters, this section assumes one operating day, namely 24 hours, as the entire study period, with the unit of time for the study being one hour. The example covered an area of 500 square kilometers, with time-dependent road speeds shown in Figure 5-2. Table 5-1 lists the base values for parameters related to vehicles and refrigerants. The food is divided into five different ranges, as shown in Table 5-2. In this example, the carrier receives 1177 orders for 20 kinds of food from 85 different retailers, with delivery time windows for each order. Figure 5-3 shows the temporal pattern of demand during the entire study period. The demand time is approximated as the middle of a time window, and demand volume is calculated in terms of kgL. As shown in Figure 5-3, shipping demand for most temperature range foods peaks from 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. Moreover, Range 3 has the most demand volume because this range contains the majority of perishable food. Range 1 is most centralized due to its shortest shelf life time and because it is affected by temperature much more than other ranges food.



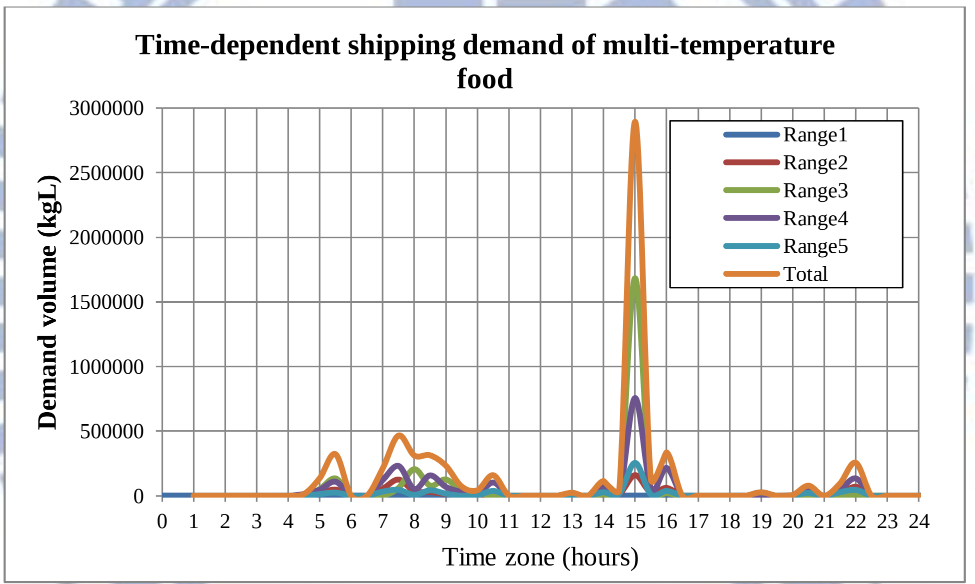
Source: This dissertation.

Figure 5- 2 Time-dependent road speed in Taipei City

Table 5- 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 used cold accumulators 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: This dissertation.



Source: This dissertation.

Figure 5- 3 Time-dependent demand for different temperature ranges food

The Chung-Hua Institution for Economic Research (2009) studied the Green Tax Reform, which is a research project entrusted by Executive Yuan. They reviewed the green tax regulation for different countries and suggested the Executive Yuan set the carbon tax rate as NT\$750/tCO_2e. Therefore, this dissertation uses this tax rate as the cost for unit emissions. Figure 5-4 (a) and (b) show the temporal distributed volume for different temperature ranges food without and with carbon tax, NT$750/t$CO_2$e, respectively. The results show that food is more mass transported under the condition that carrier is levied carbon tax than that without emissions cost, especially at 12:00-15:00. This implies that, under the carbon tax, the carrier has to deliver food by more centralized temporal pattern. Thus, the vehicle and cold box capacity utilization can be enhanced, and the emissions cost per unit item of food reduce due to economies of scale.

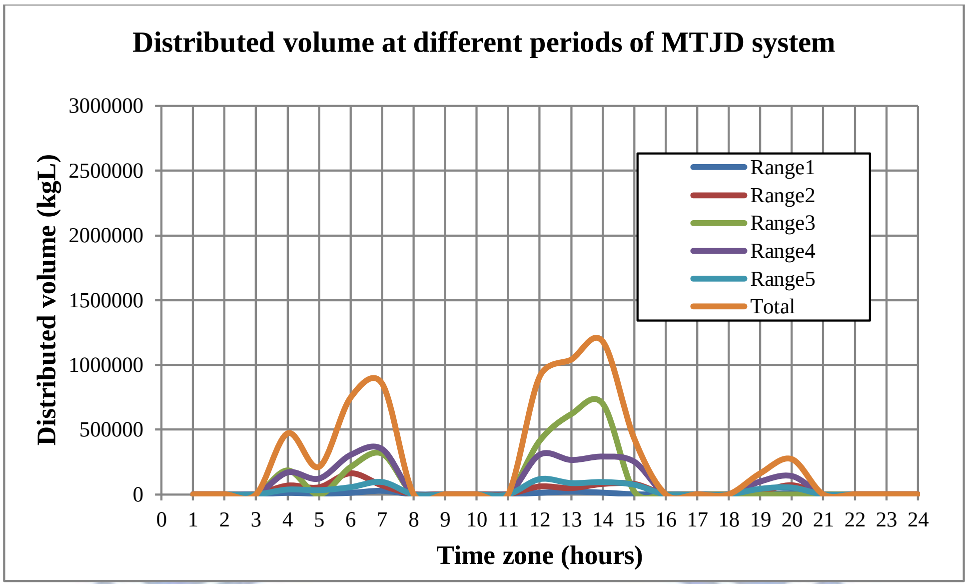
Table 5- 2 Initial values of food demand

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~-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~+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~+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~)	18	Chocolate	0.3	0.132	0.440
	19	Cookie	1.2	0.170	0.142
	20	Soft drink	1.2	1.120	0.933

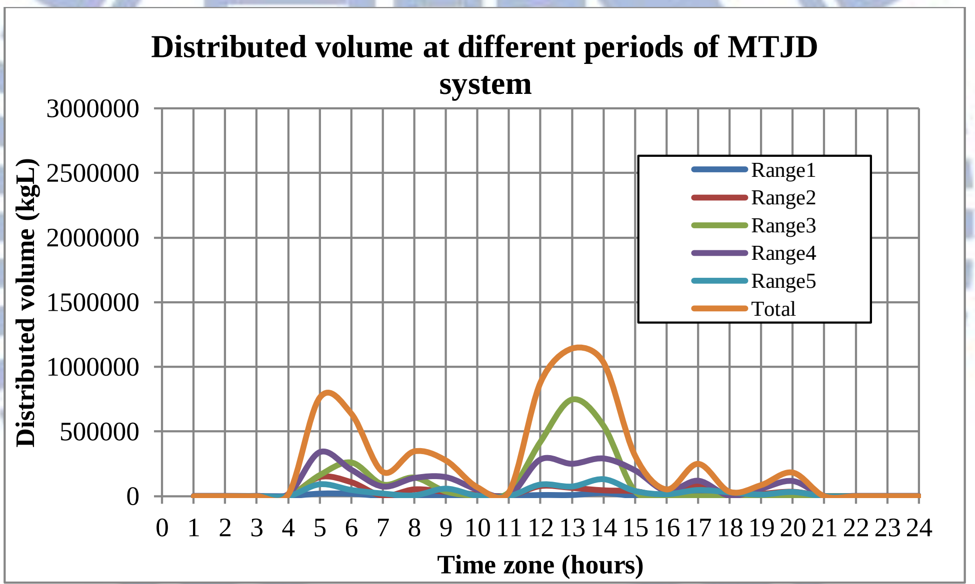
Source: This dissertation.

Figure 5-4 (b) also shows that carrier should deliver more Range 3 food at 6:00 and 13:00 and transports more other ranges food at 5:00, 12:00, and 14:00 when carbon tax is NT$750/t$CO_2$e. On the other hand, the road speed at 5:00 and 13:00 is higher than that at 6:00 and 12:00, 14:00, respectively, as shown in Figure 5-2.These imply that the carrier should deliver the food with high density at periods with high road speed. And the food with low density, that is, the food drives low energy consumption, should be transported at periods with low road speed. With high road speed, the routing time, fuel and electric power consumption simultaneously decrease. Thus, both delivery and emissions cost can be reduced. The above-mentioned appearance is much more markedly for Range 3 food than other ranges because the density of Range 3 food is highest and drives most fuel consumption than others.

Table 5-3 shows the cost structure obtained without and with carbon tax, NT$750/t$CO_2$e, respectively. In the case with carbon tax, the fuel and electric power cost both decrease when compared to the results obtained without carbon tax, from NT$122,285 to NT$108,915 and NT$82,783 to NT$78,243, respectively. On the other hand, the warehousing cost obtained with carbon tax, NT$74,015, is higher than that obtained without carbon tax, NT$74,963. However, the effect due to warehousing cost is much less than fuel cost. Therefore, the total cost obtained with carbon tax, NT$352,489, is lower than that obtained without carbon tax, NT$362,018. This implies that carbon tax does not raise carriers' cost, even helps carrier reduce delivery cost because more factors affect fuel consumption are taken into account. In such condition, the optimal delivery scheduling is programmed under better energy efficiency.



(a) Without carbon tax



(b) with carbon tax (NT$750/t$CO_2$e)

Source: This dissertation.

Figure 5- 4 Time-dependent distributed volume

Table 5- 3 Cost structure obtained with and without carbon tax

	Result obtained without carbon tax	Result obtained with carbon tax (NT$750/$tCO_2e$)
Total cost (NT$)	362,018	352,489
Transportation cost (NT$)	205,265 (56.70%)	192,735 (54.68%)
Vehicle cost (NT$)	21,400 (5.91%)	22,000 (6.24%)
Fuel cost (NT$)	122,285 (33.78%)	108,915 (30.90%)
Loading/unloading cost (NT$)	61,580 (17.01%)	61,820 (17.54%)
Warehousing cost (NT$)	74,015 (20.45%)	74,963 (21.27%)
Penalty cos t(NT$)	0 (0%)	0 (0%)
Energy cost (NT$)	82,738 (22.85%)	78,243 (22.20%)
Emission cost (NT$)	/	6,547 (1.86%)

Source: This dissertation.

Table 5-4 lists the emissions under the distributed pattern in Figure 5-4(b). As shown in Table 5-4, emissions from fuel consumption account for most percentages of the total emissions when compared to other sources. The distribution pattern in Figure 5-4(b) results in most emissions at 5:00-6:00 and 12:00-14:00 since the distributed volume at these periods are much higher than other time durations. Furthermore, the emissions from all sources at 5:00 are more than those at 6:00 because of higher distributed volume. The emissions from each sources at 13:00 are more than those at 12:00 and 14:00. However, comparing 12:00 and 14:00, the emissions from fuel consumption at 12:00 is more than that at 14:00, but the emissions from electric power consumption and refrigerant leakage at 12:00 are less than those at 14:00. As shown in Figure 5-4(b), at 14:00, the distributed Range 3 food is more than Range 4. However, the temperature for storing Range 3 food is lower than that for Range 4. That is, unit Range 3 food consumes more electric power and refrigerant than Range 4 food.

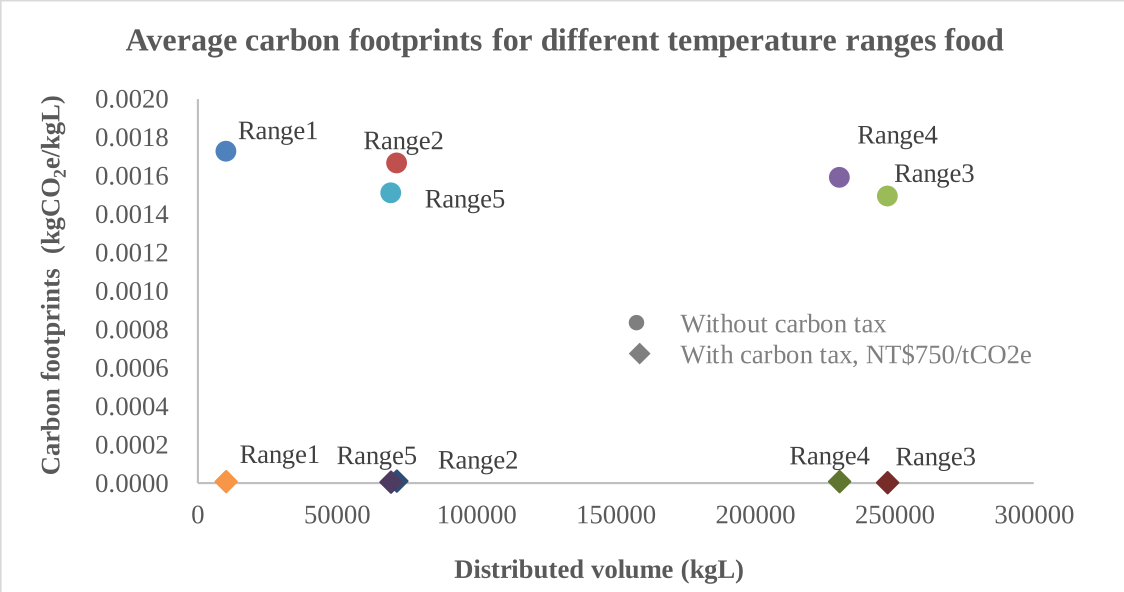
Therefore, the distribution pattern results in more emissions from electric power consumption and refrigerant leakage at 14:00. But at 12:00, the distributed Range 3 food is less than Range 4. And the density of Range 4 is higher than Range 3, as shown in Table 5-2. That is, unit Range 4 food consumes more fuel than Range 3 food. Therefore, the distribution pattern results in more emissions from fuel at 12:00. However, the total emissions at 12:00 are much more than that at 14:00.

Figure 5-5 shows the carbon footprints for different temperature ranges food without and with carbon tax (NT$750/t$CO_2$e), respectively. The average carbon footprints of food are calculated by dividing total emissions by total distributed volume in terms of kgL. The results show that the carbon footprints for each temperature range food obtained with carbon tax are markedly lower than those obtained without the green tax. Furthermore, Figure 5-5 shows the difference in carbon footprints between temperature ranges food under carbon tax also decreases markedly when compared to the results obtained without carbon tax. This is because that the model combines delivery and emissions cost makes food which drives more fuel consumption be deliver with higher road speed, as discussed earlier. Thus, the influence on emissions due to temperature range is reduced, and the difference in carbon footprints between ranges decreases. The finding implies that carrier should take into account the emissions cost while delivering the food with various characteristics jointly; then, the environment impact of low temperature ranges food can be lessened.

Table 5- 4 Emissions from different sources at different periods when carbon tax is NT$750/t$CO_2$e

Time	Emissions (unit: kgCO_2e)			
	Fuel consumption	Electric Power consumption	Refrigerant Leakage	Total
1:00	0	0	0	0
2:00	0	0	0	0
3:00	0	0	0	0
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	0	0	0
22:00	0	0	0	0
23:00	0	0	0	0
24:00	0	0	0	0
Total	8565.26	154.41	9.9	8729.57

Source: This dissertation.



Source: This dissertation.

Figure 5- 5 Average carbon footprints for different temperature ranges food

5.4 Summary

This chapter combines the delivery scheduling and emissions estimation model for the MTJD system, which is developed in Section 3.2.2 and Section 4.1, respectively. A numerical example illustrates the application of the combined model and indicates carrier should deliver heavy food at periods with high road speed. Furthermore, the results show that both delivery cost and difference in carbon footprints between temperature ranges decrease when the carrier considers emissions cost.

Chapter 6 Conclusions

This chapter summarizes the important findings as well as some managerial implications with respect each part of this dissertation. Furthermore, future research areas that extend from this dissertation and might produce interesting results are also point out.

6.1 Research summary

The purpose of this dissertation is to study the delivery scheduling and greenhouse gas emissions problems for multi-temperature food transportation, coping with the time-dependent demand and traffic condition. In view of this, a series of models are formulated in accordance with various issues emphasized. According to the issues of significance, there are three parts in this dissertation, where the study objects of the first part include fleet size and delivery scheduling under time-dependent demand. The objects of the second part contain the emissions in the MTJD and TMVD system, under minimized delivery cost. Finally, the third part focuses on the delivery scheduling under the assumption that carrier is levied carbon tax. Summaries of major contribution and important findings of this dissertation are as follows.

Part I: Fleet size and delivery scheduling for multi-temperature food transportation

(1) This dissertation formulates a mathematical programming model to solve the optimal fleet size and food departure times for jointly delivering different temperature range food. 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.

(2) With the MTJD system, the combination of temperature ranges in the vehicle can be easily changed based on demand. This characteristic allows the MTJD technique to easily deal with the stochastic and dynamic nature of the problem. Furthermore, this dissertation 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.

(3) The results show that vehicle handling cost does not affect the optimal fleet size, but vehicle idling cost has a marked influence on the optimal fleet size. As the idling cost increases, the optimal fleet size decreases at a greater rate. Therefore, this dissertation suggests carrier determines 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) The results show that, under limited fleet capacity and time-dependent shipping demand, the carrier should abandon some orders of the lowest or normal temperature range food at peak periods. Thus, other range food that yield more profit can be delivered on time and the total profit of the carrier can be maximized.

(5) The results show that huge multi-temperature shipments are delivered to a few shippers at peak periods. Therefore, this dissertation suggests carrier delivers shipments of huge size with priority at periods with peak demand because they can yield more revenue, and the cost of violating their time windows might be large.

(6) The results show that the transportation cost accounts for the highest percentage of the total cost. Moreover, the electric power cost accounts for the second highest

percentage due to the power consumed by freezers. The results also show that travel time during rush hours is longer than other periods. The findings implies that carriers should reduce travel time by avoiding routing on congested roads, especially at periods with high shipping demand. Thus, more transportation and electric power cost related to routing time and/or distance can be reduced.

(7) The results show that the cost obtained with demand-supply interaction is lower than that obtained without demand-supply interaction 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. Optimal departure time solving with demand-supply interaction results in higher profits than models without demand-supply interaction.

(8) The results show that the time window violation rate obtained with demand-supply interaction is much lower than that obtained without demand-supply interaction. The service level can be effectively enhanced after rounds of interaction, which helps maintain the carrier's shipping volume and revenue over time.

Part II: Emissions estimation for temperature-controlled food delivery system

(1) With the growing interest in reducing GHG emissions, many studies investigate energy consumption and the environmental impact of refrigerated food transportation. This dissertation formulates mathematical models to estimate and compare emissions from traditional multi-vehicle delivery and multi-temperature joint delivery systems for food. This dissertation compares the emissions for each period of the two systems under conditions of minimized delivery costs. The proposed models can analyze the uncertainty of dynamic demand, levels of traffic

congestion, and emissions.

(2) The results indicate that, as compared to the TMVD system, the MTJD system yields less total emissions by lowering fuel consumption even when it generates more CO_2e due to refrigerant leakage and emissions from electric power consumption for freezers. This dissertation suggests carriers use the MTJD system to reduce routing distances and emissions simultaneously.

(3) The results show that carbon footprints go down by a greater percentage than distributed volume raises in the MTJD system, but the influence of distributed volume on average carbon footprints is not noticeable in the TMVD system. The higher the distributed volume, the more the MTJD system can reduce the carbon footprints per unit food, which implies that the larger the carrier size, the greater the benefit to carbon footprint reduction per unit food by using the MTJD.

(4) This dissertation demonstrates how different temperature-control techniques and demand characteristics, such as food delivery time and volume, are related and considered when examining emission estimations for food delivery systems. The results of this dissertation provide an assessing-support tool that analyzes emissions from temperature-controlled food delivery system for carriers.

Part III: Multi-temperature food delivery scheduling under carbon tax

(1) For multi-temperature joint delivery, delivery scheduling is an extremely complex task due to various temporal demand patterns and delivery time windows. On the other hand, the multi-temperature joint delivery contributes a considerable amount of greenhouse gas (GHG) emissions due to fuel burn and HFCs and PFCs

generated by refrigeration. Many governments around the world has planned carbon tax for GHG emissions. For these reasons, this dissertation aims to optimize delivery scheduling for the multi-temperature joint delivery system, considering delivery and emissions cost, time-dependent demand, and various traffic congestion simultaneously.

(2) The results show that food is more mass transported under the condition that carrier is levied carbon tax than that without emissions cost. Under carbon tax, the carrier has to deliver food by more centralized temporal pattern. Thus, the vehicle and cold box capacity utilization can be enhanced, and the emissions cost per unit item of food can be reduced due to economies of scale.

(3) The results show that the carrier should deliver food with high density at periods with high road speed, and the food with low density should be transported at periods with low road speed. Thus, the routing time, fuel and electric power consumption simultaneously decrease, and both delivery and emissions cost can be reduced. The above-mentioned appearance is much more markedly for food which has highest density because it drives most fuel consumption than others.

(4) The results show that the fuel and electric power cost both decrease when compared to the results obtained without carbon tax. The carbon tax does not raise carriers' cost, even helps carrier reduce delivery cost because more factors affect fuel consumption are taken into account. In such condition, the optimal delivery scheduling is programmed under better energy efficiency.

(5) The results show that the carbon footprints for each temperature range food obtained with carbon tax are markedly lower than those obtained without the carbon tax. The difference in carbon footprints between temperature ranges food

under carbon tax also decreases markedly when compared to the results obtained without carbon tax. This dissertation suggests carrier takes into account the emissions cost while delivering the food with various characteristics jointly. Thus the environment impact of low temperature ranges food can be lessened.

6.2 Extensions for future research

The extensions from the study results for future research are discussed as follows.

(1) This dissertation assumes the carrier seeks to optimize fleet size, taking into account revenue, vehicle holding cost, and vehicle idling cost. Although this dissertation analyzes the variation of shipping volume under demand-supply interaction, the case study shows that the optimal fleet size is still insufficient at periods with peak demand. Future studies may extend this study by developing scenarios to help carriers satisfy all shipping demand. For example, the future studies may explore the strategy that carrier outsources part of shipping services to other logistics companies.

(2) In this dissertation, the explored shipping demand only contains the multi-temperature food. Due to the time-dependence of multi-temperature food, at some period, not all of the vehicles are dispatched. Future research may extend the numerical example by considering non-perishable cargos and exploring how to maximize the vehicle utilization at all periods.

(3) In this dissertation, the demand of multi-temperature food from different shippers is independent on each other. However, some abnormal event may occur and have impact on multi-temperature food demand. For example, the competition between

retailers and food safety news often changes the food demand. Future research may address these issues by studying the various market and exploring how to adjust the fleet size and delivery scheduling in response to competition and safety crisis of food.

(4) For shipping charges for different temperature ranges, this dissertation only considers the delivery cost and shipper's willingness to pay as the key components. The competition between different carriers is not taken into account. Future research may extend the model by formulating the influence of competition on shipping charges of multi-temperature food.

(5) From the view of shippers, this dissertation describes the trade-off between transportation and inventory cost by shipping charges for different alternatives, delivering on the day of ordering or on the day after ordering. Furthermore, this dissertation analyzes the variation of consigned volume for each temperature range under demand-supply interaction. This dissertation assumes the shippers' willingness to pay depends not only on delivery time and shipping charges but also on costs other than transport and acceptable profits for selling food. The higher the shippers' acceptable profit, the lower the shipper's willingness to pay, and the lower the carrier can charge. However, for a carrier, it is difficult to know the information about shippers' other costs and acceptable profits. This dissertation explores the above-mentioned issue by exogenous and binary variables which describe shippers' acceptable profits and whether the carrier's service level (shipping charges and delivery time) satisfies shippers, respectively. Future studies may extend the research by exploring how to estimate shippers' (retailers') cost and acceptable profit from the view of a carrier, with the methodologies like shadow price or mathematical programming.

(6) This dissertation deals with the delivery scheduling by multi-periods approach; then, the difference in road speed between periods can be taken into account. However, the traffic condition may be affected by stochastic events. Future studies may extend this research by referring Hsu et al., (2007) and replacing the road speed variable with a stochastic function.

(7) This dissertation 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.

(8) The numerical examples in this dissertation are based on the metropolis with a study duration of one operating day. Future research may apply the model to outskirts and extend the study duration beyond one day. On the other hand, in the case studies, the food demand data is suppositional because the real data is internal information of logistics companies; it is difficult to collect. Future study may extend the case study by more sensitivity analysis or using real data collected from logistics companies.

(9) For emission cost, this dissertation assumes the carrier is levied by a fixed carbon tax rate. The emission cost of a carrier is the product of carbon tax rate and emission volume. Therefore, the higher the carbon tax rate or the higher the emissions the transportation system generates, the more the emissions cost of the carrier. Under the objective of minimizing cost, when the carbon tax rate increases, the optimal delivery scheduling results in less emissions, and the cost related to

energy and refrigerant consumption decrease simultaneously. However, in some countries, governments set emissions upper bound or build allowance trade markets which make the carbon price vary with time. Future research may extend the model by adding a constraint for emissions upper bound or a function for dynamic carbon price.

(10) This dissertation assumes the emissions due to back-haul of vehicles are equal to that of delivery process. However, the vehicle weights are changed after unloading food. Future studies may expand the model and explore the reverse logistics issue in the multi-temperature transportation system. Furthermore, this dissertation focuses on emissions which depend on delivery scheduling; future studies can expand the model to discuss emissions due to inventory and retailers' activities in the whole multi-temperature food supply chain.

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PUBLICATION

Journal Papers

1. Chaug-Ing Hsu and **Wei-Ting Chen**, (2014). Optimizing fleet size and delivery scheduling for multi-temperature food distribution. *Applied Mathematical Modelling*, 38, 1077-1091. (SCI, Impact factor: 1.706, 2012)

2. Chaug-Ing Hsu, **Wei-Ting Chen**, Wei-Jen Wu, (2013). Optimal delivery cycles for joint distribution of multi-temperature food. *Food Control*, 34, 106-114. (SCI, Impact factor: 2.738, 2012)

3. Chaug-Ing Hsu, Yu-Hua Chen, **Wei-Ting Chen**, (2013). A study on airlines differentiated cargo service strategies. *Transport Policy*, 25, 101-110. (SSCI, Impact factor: 1.541, 2012)

Under review

4. **Wei-Ting Chen**, Chaug-Ing Hsu, (2013). Greenhouse gas emissions estimation for temperature-controlled food distribution. Paper submitted to *Journal of Cleaner Production.* (SCI, Impact factor: 3.398, 2012)

Working paper

5. **Wei-Ting Chen**, Chaug-Ing Hsu. Optimal delivery scheduling for multi-temperature joint distribution system under carbon tax.

Conference papers

1. Chaug-Ing Hsu, **Wei-Ting Chen**, (2011). Multi-objective programming in delivery cycles determining for multi-temperature joint distribution system. Paper presented at the 7th *International Congress on Industrial and Applied Mathematics (ICIAM)*, Vancouver, Canada, July 18-22, 2011.

2. Chaug-Ing Hsu, **Wei-Ting Chen**, (2011). Green house gas emissions estimation for multi-temperature joint distribution system. Paper presented at the 7th *International Congress on Industrial and Applied Mathematics (ICIAM)*,

Vancouver, Canada, July18-22, 2011.

3. Chaug-Ing Hsu, Yu-Hua Chen, **<u>Wei-Ting Chen</u>**, (2009). The study on airlines differentiated cargo service strategies. Paper presented at the 56th *Annual North American Meetings of the Regional Science Association International*, San Francisco, U.S.A., November 18-21, 2009.

4. Chaug-Ing Hsu, **<u>Wei-Ting Chen</u>**, (2008). The study on urban logistic joint system for temperature-controlled goods. Paper presented at the 55th *Annual North American Meetings of the Regional Science Association International*, New York, U.S.A., November 19-22, 2008.

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